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VISUALIZATION OF SPATIO-TEMPORAL INFORMATION FOR PERSONAL PERFORMANCE ANALYSIS IN GAMES

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Resumo

Nos últimos anos, o fenómeno do *e-sports* (desportos eletrónicos) tem vindo a crescer. Consequentemente, o interesse em videojogos *online* também aumentou drasticamente. Hoje em dia, os grupos que demonstram interesse nesta área vão muito para além dos jogadores. Em contextos profissionais, existem analistas e treinadores que são responsáveis por guiar e aconselhar equipas de jogadores que competem em torneios e ligas oficiais com prémios monetários. Por outro lado, em contextos casuais, é cada vez mais comum existirem indivíduos que assistem a partidas de jogos online como uma fonte de entretenimento. Estes indivíduos encaixam-se num novo grupo emergente chamado de espetadores. Existem hoje em dia plataformas como a Twitch ou o YouTube Gaming, dedicadas exclusivamente à cultura dos videojogos, onde os indivíduos pertencentes a este grupo podem observar jogadores a transmitir a sua experiência de jogo.

Um dos géneros de jogos mais populares, e com maior audiência no mundo do *e-sports* é o MOBA (Multiplayer Online Battle Arena), também conhecido como ARTS (Action Real-Time Strategy). Este tipo de jogos é caracterizado por ser jogado por duas equipas, tipicamente com cinco elementos cada, que lançam ataques coordenados na base da equipa adversária com o objetivo de a destruir. As partidas deste tipo de jogo podem durar uma quantidade de tempo ilimitada, sendo que, tipicamente, não ultrapassam os 30 a 40 minutos. Cada um dos jogadores pode escolher uma personagem, de um conjunto com várias dezenas de possibilidades, que o irá representar durante uma partida. Estas personagens possuem um conjunto único de habilidades que podem ser utilizadas para interagir com os outros jogadores e com os elementos do ambiente virtual.

Tal como em desportos tradicionais, durante uma partida deste tipo de jogos, existem vários eventos que são de interesse para jogadores, espetadores, treinadores e analistas. Existem eventos que são comuns entre estes dois contextos, tais como, a posição de um jogador num determinado instante, ou o caminho que este fez do ponto A até ao ponto B. No entanto, existem também eventos que são mais específicos dos jogos virtuais, tais como, a posição onde um jogador morreu ou a destruição de certas estruturas defensivas. De qualquer modo, estes eventos podem ser analisados de modo a tentar extrair padrões de comportamento e estratégias de jogo que são utilizadas.

A grande diferença entre estes contextos, é que com a evolução tecnológica, tem-se tornado cada vez mais fácil e comum a instrumentação do código fonte dos videojogos com técnicas de telemetria para recolher dados sobre estes eventos. Por sua vez, isto faz com que, à medida que o tempo passa, sejam gerados grandes volumes de dados que podem ser utilizados para análise. Para poder utilizar estes dados para análise de um modo mais eficaz e eficiente, é necessário explorar diversas técnicas de visualização, sejam elas existentes ou novas, de modo a perceber quais é que são mais adequadas para aplicar ao tipo de dados disponíveis no contexto da análise de videojogos.

Estudos anteriores relevam que, apesar das diversas técnicas de visualização que podem ser aplicadas, especialmente no âmbito da análise de dados espácio-temporais, tanto a indústria dos videojogos, como as plataformas dedicadas às comunidades de jogo, praticamente não tiram partido do uso das mesmas. Contudo, tanto a comunidade cientifica como as equipas de desenvolvimento de videojogos, têm começado a utilizar algumas destas técnicas, o que demonstra interesse em incorporá-las no contexto da análise de videojogos. A grande maioria das técnicas aplicadas neste âmbito consiste em vários tipos de gráficos e tabelas que são utilizados para demonstrar estatísticas e dados temáticos. Algumas plataformas tiram partido das componentes espaciais dos dados, para utilizar diversas técnicas baseadas em mapas, tais como *heatmaps* e mapas de coropletas. No entanto, apesar de algumas destas técnicas utilizarem a componente temporal ou a componente espacial dos dados, é difícil encontrar exemplos da utilização de técnicas de visualização no contexto da análise de videojogos que utilizem ambas as componentes em simultâneo.

Tendo isto em conta, o foco deste trabalho consiste em tirar partido da vasta popularidade dos videojogos, combinada com a grande quantidade de dados telemétricos que estão disponíveis, com o objetivo de estudar o uso de diversas técnicas de visualização aplicadas no contexto da análise do desempenho de jogadores utilizando tanto as componentes espácio-temporais dos dados, assim como as componentes temáticas. Nesse sentido, durante este trabalho, foi desenvolvido o protótipo VisuaLeague, que incorpora diversas técnicas de visualização, em particular mapas animados, que permite aos utilizadores analisarem o desempenho de jogadores em partidas de League of Legends. A escolha deste jogo em particular como caso de estudo, deve-se ao facto de ser um dos mais populares jogos do género MOBA e, consequentemente, existir uma grande quantidade de dados disponíveis relativos a partidas do mesmo. Devido à sua popularidade, é também fácil encontrar indivíduos interessados em colaborar nas decisões que envolvem o processo de desenvolvimento.

A solução desenvolvida foca-se maioritariamente na utilização de técnicas de visualização que permitam observar dados que incorporem componentes que evoluam ao longo do tempo. Em particular, neste protótipo é utilizada a técnica de mapas animados para visualizar as posições e as trajetórias de até dois jogadores de equipas adversárias. É também possível, através desta técnica, visualizar os vários eventos que decorrem durante uma partida, tais como a destruição de estruturas defensivas ou a mortes dos jogadores. Esta técnica é complementada por um conjunto de gráficos, tabelas e outras visualizações que, apesar de não incorporarem a componente espacial dos dados, permitem visualizar a evolução ao longo do tempo de diversas métricas temáticas que são tipicamente utilizadas noutras plataformas dedicadas à analise do desempenho de jogadores de League of Legends.

Posteriormente, foi realizado um estudo com o objetivo de avaliar as técnicas utilizadas, assim como para perceber qual o papel que os dados espácio-temporais têm na análise do desempenho dos jogadores, quando feita por outros jogadores. Os resultados mostram que as técnicas utilizadas, nomeadamente o mapa animado, são adequadas tanto para transmitir a informação espácio-temporal associada ao movimento dos jogadores e aos eventos que decorrem durante uma partida, assim como a informação temática que lhes está associada. Os resultados mostram ainda que a utilização de técnicas não estáticas, ou seja, que evoluam ao longo do tempo, é uma mais valia, pois permite a extração de padrões de jogo e estratégias utilizadas, o qual não é possível com as técnicas tipicamente utilizadas neste contexto. Para além disso, os resultados apontam para a elevada importância da informação espácio-temporal para análise do desempenho dos jogadores, sendo que estas permitem uma análise mais detalhada.

Apesar do trabalho desenvolvido ser uma boa base para novos trabalhos na área, os resultados obtidos apontam para a necessidade de melhorar a solução criada. Deste modo, como trabalho futuro, o primeiro caminho a tomar será resolver o problema de sobreposição dos eventos no mapa animado, de modo a garantir que este fator não perturbe a análise efetuada pelos utilizadores. Posteriormente, será também interessante incorporar múltiplos jogadores em simultâneo (mais do que dois), quer na visualização do mapa, quer nas restantes visualizações. É também necessário abordar os problemas mencionados na utilização do *slider* que controla o mapa animado, de forma a adaptar de melhor forma a técnica às necessidades dos vários utilizadores. Finalmente, é importante explorar outras formas de gerar as trajetórias dos jogadores que aumentem a precisão das mesmas tendo em conta a informação disponível. Se possível, na ausência da disponibilização de mais informação, seria ideal desenvolver mecanismos que permitissem obter dados que possam ser incorporados no mapa animado de forma a melhorar a análise disponibilizada pelo mesmo.

Palavras-chave: interação pessoa-máquina, dados espácios temporais, técnicas de visualização, mapas animados, League of Legends

Abstract

In recent years, the phenomenon of *e-sports* has been a growing trend. Consequently, the interest in online video games from both players and spectators has significantly increased, as watching other individuals play has become one of the main sources of entertainment for these groups.

One of the most popular genres in *e-sports* is the MOBA (Multiplayer Online Battle Arena). Much like in traditional sports, during a match there are various types of events that are of interest for players, spectators, coaches and analysts. These events can range from a player's position at a given time or the path they took from point A to point B, to more specific game events, such as, the position of a player's death or the destruction of certain defensive structures.

With the evolution of technology, it has become easier and more common to instrument video game code with telemetry techniques to record these events, which in turn, leads to large volumes of data that can be collected over time. To more effectively and efficiently analyze this data, it is necessary to explore existing and new visualization techniques to understand which are better suited to use in the context of video game analysis.

Previous research reveals that, despite the many different visualization techniques that can be applied, especially to spatio-temporal data, the video game industry barely takes advantage of most of them. However, developers and researchers alike, have started to use some of these techniques, which shows interest in applying them in the context of video game analytics.

The focus of this work consists on taking advantage of the popularity of these video games, combined with the large amount of telemetry data available, to study the use of several visualization techniques, applied in the context of player performance analysis using spatio-temporal and thematic data. For this purpose, the VisuaLeague prototype was developed, which incorporates some visualization techniques, namely animated maps, to allow users to analyze player performance in League of Legends matches. Posteriorly, a study was conducted, aimed at evaluating the techniques used, as well as the role of spatio-temporal data in player performance analysis. The results support the adequacy of using the animated map technique to convey information to users in this context. Moreover, they also point out towards a high degree of importance regarding the spatio-temporal components of the data for player performance analysis.

Keywords: human-computer interaction, spatio-temporal data, visualization techniques, animated map, League of Legends

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Chapter 1

Introduction

1.1 Motivation

In recent years, the phenomenon of *e-sports* has been an increasingly growing trend [1, 2]. Not only the amount of people playing the game has increased substantially but, in response to that, well established companies have started to take more interest in investing in this area [3]. In turn, this lead companies, such as Riot Games[1] and ESL[2], to create professional leagues that feature tournaments with monetary prizes. These initiatives also provide the opportunity for players to pursue professional careers with a stable source of income. Well-known companies, such as Samsung, even have their own fully sponsored team[3]. Some of these players even get the chance to pursue a career related to gaming after they retire from professional play [4]. There are also amateur leagues, such as the one provided by ESL, that any player can join for a chance to win prizes. These leagues can also serve as a starting point for casual players to become professionals, as teams are always interested in recruiting new talents.

With this growth in popularity, not only the number of players has risen but, new groups have emerged that take interest in video games: analysts, coaches and spectators. All these groups have different reasons why they take interest in video games and, as such, they all have different needs when it comes to interacting with video game data.

Similarly to traditional sports, in *e-sports* there are a great number of spatio-temporal events that are interesting to analyze. These events can range from the position of players at a certain time, or the path they take from point A to point B, to more specific game events like the location of a player's death or the items bought during a match. The main difference between traditional sports and *e-sports* is how easy it is to

[1] http://www.lolesports.com/en_US/
[2] https://www.eslgaming.com/
[3] http://lol.gamepedia.com/Samsung_Galaxy_White

use telemetry techniques to record data for further analysis [5, 6]. Consequently, this generates a large volume of data that can be used to analyze the performance of players.

Nowadays, this analysis is of great importance in both professional and personal contexts. For example, analysts and coaches want to study this data to understand how their team and the opposing teams are playing, in order to identify limitations and create new and improved strategies. On the other hand, players and spectators want to know how their friends and favorite professional players are performing compared to their peers. In addition, these games usually classify their players based on their expected skill. As such, personal improvement is also an important goal for most players, even more casual ones, as they strive to improve their ranking. Professional team owners are interested in player analysis as well, to scout for new members and improve their rosters. From a developer point of view this data can also be of great interest. By analyzing this data, developers can assess their games in respect to game design decisions and their effect on the player base [5–7]. This can help balance out gameplay and aid in keeping the companies much closer to their customers, allowing them to provide a semi-constant stream of new content for players, which in turn makes these more loyal to the game, leading to increased revenues. Although these groups may approach video games differently, evaluating player performance seems to be a common denominator.

With the large amount of data collected via telemetry techniques, it may prove difficult to perform a productive analysis to extract relevant conclusions and patterns. Therefore, it is of extreme importance to understand which visualization techniques are most adequate to apply to the type of information that is being extracted, especially when it comes to spatio-temporal data [5], since not every approach can provide the levels of insight that individuals are seeking. It is then necessary to study which visualization techniques are better qualified to be used with the available data, while at the same time meeting the needs of the groups mentioned earlier, particularly focusing on players.

1.2 Goals

The main goal of this project is to take advantage of the ever-growing telemetry data collected from video games, giving special attention to the spatio-temporal components of this data, to explore visualization techniques that assist players, coaches and analysts on the task of evaluating player performance. The data used to explore these techniques will be from matches of the game League of Legends (LoL) provided through the Riot Games API. This choice is justified by the immense popularity of the game which leads to large quantities of data being constantly generated for analysis. Regular updates to the game contribute to shifts in gameplay and decision making, which also makes frequent analysis yield new and interesting results.

The objective of this approach is to get a better understanding of which visualization techniques are more suited to handle this type of data, while at the same time creating a tool for player performance analysis, that meets the needs of players, and that can easily be adapted to other games of the same genre. This work will also study the importance of the spatio-temporal components of the data when analyzing player performance.

1.3 Contributions

The main contributions of this work can be summarized as following:

- The study and discussion of previous research focused on different types of analysis and visualization techniques, applied in the context of video games, and how these subjects influence the current state of video game analytics, in particular, the analysis of player performance and behavior.
- A prototype, named VisuaLeague, that uses multiple visualization techniques, with a focus on animated maps, to allow users to visualize spatio-temporal and thematic data with the purpose of analyzing player performance.
- A user study that focuses on evaluating the adequacy of the visualization techniques implemented, as well as the importance of spatio-temporal data in the context of player performance analysis.
- An article describing the work developed during this thesis and its objectives for the conference - *Encontro Português de Computação Gráfica e Interação* (EPCGI) 2017: Pedro Vieira, Tiago Gonçalves, Ana Paula Afonso, Maria Beatriz Carmo. Animated Maps for Analysis of Personal Performance in Games.

1.4 Document Organization

The remainder of this document is organized as follows:

Chapter 2 provides a review and detailed analysis of the relevant existing work in the literature. In particular, this chapter focuses on the analysis of gameplay data. It describes the current state of telemetry in video games, followed by a presentation of the nature of the data collected through these methods and some of the analysis that can be performed. After that, it focuses on describing the current visualization techniques and approaches employed in the context of video games.

Chapter 3 presents a description of the game League of Legends, as well as a detailed explanation of all the telemetry data that can be obtained through the Riot Games

API. After that, it presents an analysis of existing applications directed at analyzing player performance. Lastly, it describes the application developed during this work, VisuaLeague, by presenting the technologies used, as well as the development process. This chapter finishes with a description of all the features of the application.

Chapter 4 presents the evaluation process used to analyze VisuaLeague. More specifically, it describes the informal interviews conducted and presents the user study that evaluates the visualization techniques developed, and the importance of the spatio-temporal components of the data in the analysis of the performance of players.

Chapter 5 finalizes this document by describing the main conclusions drawn from this work, presenting also the most promising and challenging research opportunities for future work.

Chapter 2

Related Work

Visualization techniques have always been an integral part of video games. They can be observed across all game genres [5, 6, 8, 9], either explicitly implemented in the game itself, much like the well-known health bar (Figure 1), or outside the game environment in more traditional ways, such as plots or maps, as can be seen in various game community dedicated platforms (Figure 2). One important area in which these visualization techniques are applied is the analysis of player behavior and decision making [6, 10, 11]. Behavior can be considered as a successive sequence of actions within a specific context. Understanding the behavior of players, and more importantly the reasons that lead to the actions performed, can be of interest when analyzing game related data. The use of techniques that can incorporate the movement of the players over time, as well as the virtual world that surrounds them, and the interactions with other players, are of special interest when the analysis is focused on player performance and behavior.

Figure 1 – Health and mana bars[1]

In recent years, the advances in technology have made telemetry techniques more accessible for the collection of gameplay data from any video game [2, 7]. Consequently, this abundance of data, combined with the increased popularity of video games, fostered the interest of players and other individuals to analyze it. Therefore, it is necessary to provide methods that facilitate and improve this analysis, by means of adequate visualization techniques.

[1] https://www.leagueoflegends.com

By itself, an analysis focused on the spatio-temporal components of the data already supports complex types of analyses tasks, such as the study of the players' trajectories, which can, for instance, help understand where and how often a player visited a certain location. However, when combined with thematic data, this analysis can be further expanded, as it can provide additional insights that can help justify the reasons for certain decisions made by players.

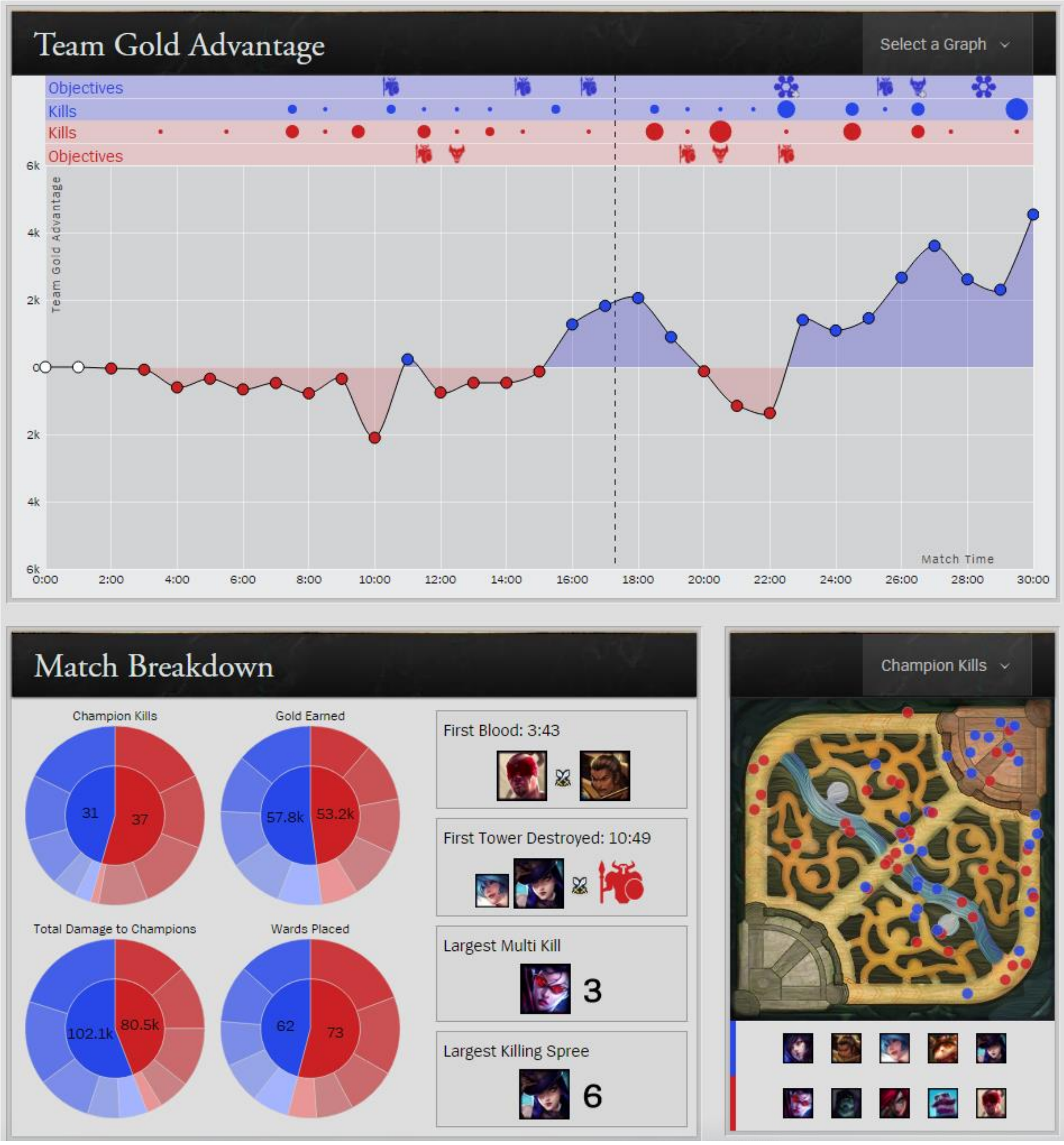

Figure 2 – League of Legends Match History[1]

This chapter outlines the most relevant research done regarding these techniques, especially in the context of video games. The first section covers topics related to game data collected via telemetry. The second section addresses the current directions and

[1] http://matchhistory.euw.leagueoflegends.com/

common visualization techniques applied in the field of video games, as well as a design framework that can be used to classify any specific visualization technique.

2.1 Gameplay Data Analysis

Gameplay data can be extremely heterogeneous and, thus it can be analyzed using several distinct methods [6, 13, 14]. Gathering this data is an important step in the process of creating visualization techniques. Before the beginning of the design process, the data to be visualized must be carefully analyzed, in order to understand which techniques should be applied. It is also important to take into consideration the target audience so that these techniques can be adjusted to meet their requirements.

2.1.1 Telemetry in Video Games

Telemetry can be defined as the use of various instruments and sensors to remotely collect real-time measurements [6]. With the technological advances over the recent years, the practice of instrumenting the source code of video games with telemetry techniques to obtain gameplay data has become increasingly more common [5, 6]. This opens new possibilities for the assessment of games through the continuous and unobtrusive monitoring of in-game behavior [7].

With the growing popularity of online video games, the number of people interested in the analysis of telemetry data has also increased. On one hand, the developers of a game are interested in how the players are interacting with their game and how they can adapt it to enhance player experience and increase revenues [5–7]. On the other hand, players are increasingly more interested in being a part of gaming communities for competitive multiplayer games, that use statistics and visualizations to allow users to compare their performance with each other, improve their skills and share gameplay experiences [6]. There is also a relatively recent group that has emerged with interest in this data, the spectators. Although this group is mainly constituted of players, its main interests may diverge. Some of them can simply be interested in improving their own gameplay, by learning through the observation of the actions and strategies that professional or other higher ranked players perform, while others are interested in observing other individuals' gameplay as a recreational activity to pass the time (as one would by watching TV). Be it for learning or leisure, their main activity as spectators is to watch other people play video games: either players sharing their gameplay via platforms, such as Twitch[1] or YouTube Gaming[2], or live streamed international professional tournaments [11].

[1] https://www.twitch.tv/

[2] https://gaming.youtube.com/

Two types of information can usually be collected from gaming sessions: system and player-derived telemetry data [13]. System-derived telemetry is typically used to monitor game systems and to perform network balancing, to improve player experience [13]. Developers are the main group interested in this type of data. Player-derived telemetry is the focus of this work and is typically used by a wide range of individuals. This data contains information about gameplay and the actions taken by the participants of a game.

Depending on the genre, different types of information may be collected: a First-Person Shooter (FPS) game may record information about the weapons used by a player, while a Multiplayer Online Battle Arena (MOBA) game may record information related to the amount of in-game currency a player collected over time. The genre and content of the game dictates what information is present in the recorded telemetry data [6, 15, 16], hence different games will most likely have very distinct data sets. However, some data is generally recorded across most genres, such as the position over time of the in-game representations of the players (commonly known as avatars) or the location of a player’s death.

Among the most interesting and relevant aspects of player-derived telemetry data, most notably in spatio-temporal data, is the ability to evaluate not only the end results of a game or match, but also visualize all of the intermediate states that players experienced [7]. This allows for adoption of innovative approaches using visualization techniques to analyze player experience, performance and struggles.

However, it is also important to note that, when possible, telemetry data should be accompanied by qualitative data to get a better understanding of a player’s experience, since quantitative data may not provide insight into questions such as “is it being fun?” [5]. Furthermore, this qualitative data can help researchers and developers understand what metrics are more important to users, in order to direct visualization techniques at those components of the data to improve the analysis process.

Although most companies still developed their in-house system to precisely meet their requirements, some generic dedicated systems targeted at recording telemetry data have been developed [13, 14, 16]. Either way, these systems must remain as unobtrusive as possible to not disrupt gameplay and thus player experience. It is also important to note that they should be as efficient as possible from a network use standpoint to prevent game lag and disruption. Consequently, developers should aim at implementing telemetry techniques that meet all these requirements, while at the same time recording as much relevant data as possible for analysis.

2.1.2 Nature of Video Game Telemetry Data

The complexity of modern video games translates directly into a complex data set that can be extracted from them. This data is usually divided in two categories: spatial data, such as location of a player, and non-spatial data, such as health and in-game currency [13]. This distinction is important as it further emphasizes the importance that movement and position have in games and their analysis. A distinction can also be made in regards to how often a metric is recorded: frequently or event-triggered [5, 7]. A good example of frequently recorded metrics is player position, while collecting an item or killing another player can be considered as an event-triggered metric. Continuously recording spatio-temporal data can be very important as it can provide high detail on player behavior analysis, e.g., create a highly accurate representation of player movement. However, the type of information recorded via telemetry must be carefully selected so it does not result in too much unused data, preventing this way the use of extra resources (network and storage) that could be better applied elsewhere.

Most, if not all, digital games involve some sort of spatial operation, i.e., some type of movement across a platform or virtual world. These can range from simple point-and-click vector mechanics (Figure 3) to more advanced navigation in 2D/3D environments (Figure 4) [13]; therefore, this dimension is often the target for analysis and evaluation. Since all gameplay occurs over time it is also common to integrate this dimension into the analysis, at least when moving past simple aggregations and visualizations of telemetry data [13].

Figure 3 – Point-and-click game: Indiana Jones and the Fate of Atlantis [1]

[1] http://www.gamefaqs.com/pc/562678-indiana-jones-and-the-fate-of-atlantis/images/219

Figure 4 – Game with a complex 3D environment: Counter--Strike: Global Offensive [1]

Based on the spatio-temporal data collected, it is possible to answers four types of questions when a player acts: what is happening?; where is it happening?; when is it happening?; and to whom is it happening? [13]. Although these questions can, often, be answered through the analysis of the players' spatio-temporal locations, they can also benefit from the inclusion of thematic data related to the game, in general, and those locations and events, in particular [13]. For instance, a player might have died in a specific place at a specific point in time, but it might also be of interest to record what killed him, to perform a deeper analysis of the situation and allow for the creation of strategies that can overcome his difficulties.

This spatio-temporal data can be used to perform various types of analysis, such as trajectory analysis [9]. A trajectory consists in the description of the evolution of a moving object's spatial properties over a period of time [15, 17], for example the navigation of a player through a game level. The analysis of these trajectories consists in the study of the path that a moving object follows through space as a function of time. Nevertheless, it is important to notice that the analysis of any given trajectory can be performed in various ways. For instance, it is possible that the focus of the analysis is the position of the player(s) when certain events happen, as a means of analyzing his/her contribution to that event. On the other hand, it is also possible to focus instead on the sequence of actions performed by the player(s), to extract behavior patterns in certain zones of the map during a specific period [18] .

[1] http://www.tobyscs.com/csgo-viewmodel-script/

Although they are applied in different contexts, the analysis of the trajectories of players in the virtual world is not completely different from the analysis of the trajectories of humans in the real world [18, 19]. Similarly to a *real-world* scenario, where monuments can be considered points of interest, in the context of video games, defensive structures or the various jungle monsters can be considered as such as well. A parallelism can also be made between events in the *real-world*, such as a taxi driver dropping a passenger, or a football player scoring a goal, and events in the virtual environment, such as a character's death or the destruction of defensive structures. On both analysis, the study of the trajectories of individuals has the potential to extract behavior patterns that are useful to adapt certain paradigms to the requirements of users. Therefore, the results obtained in studies conducted with this data can (and should) be taken into consideration in the context of analyzing video games.

As an example of studies conducted in *real-world* environments, J. Gudmundsson and T. Wolle [10] created a tool aimed at analyzing the performance of football players. This tool analyzes the trajectories of players to identify the most common movement patterns of a single player or several players, and to analyze those players' passing ability. Furthermore, it can identify correlations between clusters of trajectories to allow analysts, for instance, to study how units in the team move together, for example, the defensive line, or the left winger and the left defender [10]. P. Coulton *et al.* [11] also developed a prototype capable of using trajectory analysis to study the behavior of players in a pervasive location-based game inspired by the traditional Pac-Man. The authors were able to use the developed tool to identify different patterns among players filling different roles in the game.

The typical uses of trajectory analysis in the context of video games are illegal bot program detection, group behavior examination and the study of player tactics [13]. It can also help developers understand if players are adapting according to design changes, as well as guide players by allowing them to understand if they are taking optimal paths to achieve the intended goals. Displaying many individual paths can however result in overlapping and visual clutter which, in turn, may hinder the analysis. Therefore it is important to apply appropriate aggregation techniques to facilitate the investigative process [5]. Usually, when analyzing spatio-temporal trajectories, other information, such as health, ammo and interactions with other players, is also displayed alongside the spatio-temporal trajectories to improve this analysis. In Figure 5 we can observe an application of trajectory analysis for illegal bot detection [20]. As the figure suggests, there is a visible difference between the behavior of bot programs ((b), (c) and (d)) and the behavior of human agents ((a)). The former has a tendency to be more predictable and repetitive depending on the purpose of the bot program, whereas the former is more erratic and dispersed, which is comparable to the natural movement of humans.

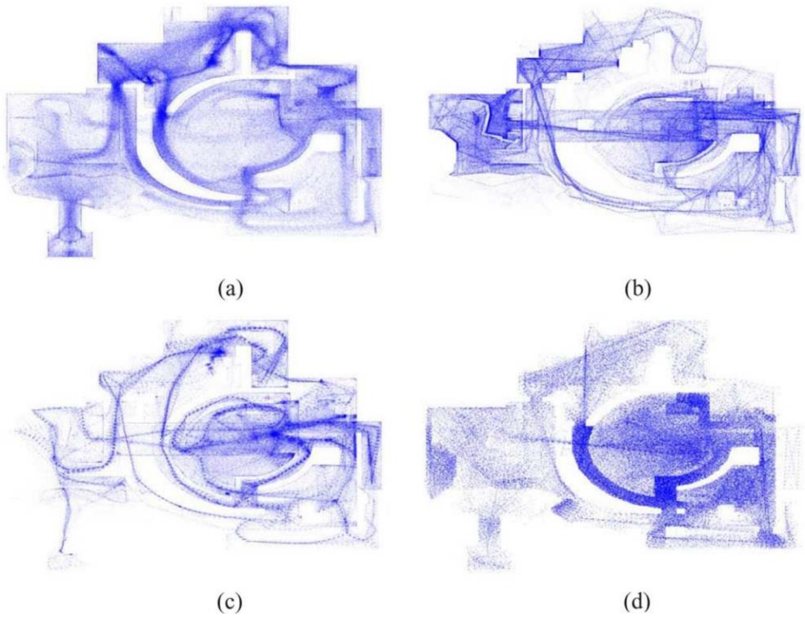

Figure 5 - Trajectories for the map "The Edge", from the popular FPS game Quake 2, for players belonging to the following categories: (a) human, (b) CR Bot, (c) Eraser Bot, and (d) ICE Bot [20]

The analysis of trajectories, particularly in game environments, has established types of patterns which are indicative of specific trajectory behaviors like tracks, flocks and leadership patterns [13]. A track describes a player having a constant movement in line within a certain area, e.g., a set of players moving on a straight line within a certain area. A flock describes a set of players moving as a unit, in such a way that all the members are within a certain spatial range at each point in time (similarly to a flock of birds). In a leadership pattern, at some point in time, players might join the movement of a leading player. This analysis, when combined with other game thematic data, is capable of revealing the reasons behind these movements patterns. In other words, it allows analysts to study where players travelled to, how they travelled and why they traveled that way.

A relevant example of the aforementioned fact consisted in the study conducted by J. Miller and J. Crowcroft, where data from the game World of Warcraft (WoW) relative to the trajectories taken by avatars in the Arathi Basin battleground was used to analyze player behavior [21]. During this study, spatio-temporal movement data was combined with activity patterns to detect specific strategies within a game. This activity recognition technique can also help detect uncounterable strategies to balance gameplay. The results showed that players who participated in that battleground tend to belong to one of three groups based on their movement patterns and in-game purpose, as exemplified in Figure 6.

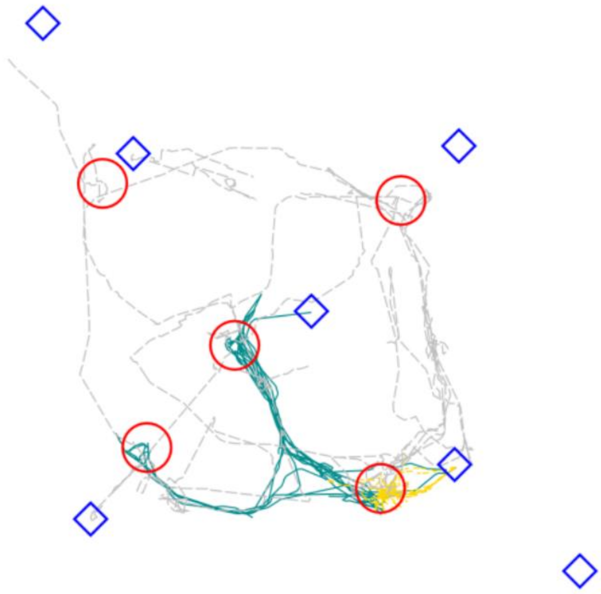

Figure 6 - Movement of three categories of players in the Arathi Basin battleground: Guard (yellow), Wanderer (grey) and Patroller (green) [21]

Behavioral analytics is an area of research that can take advantage of spatio-temporal data. This category represents a mixture of methods focused on the overall goal of delivering models to describe a set of actions in a certain context [13, 17]. The majority of methods that fall under this category of analysis describe the behavior of game entities in an isolated view, however, most of the relevant actions a player takes are strongly dependent on the behavior of other players and consequently it must also be considered. Drachen *et al*. [8] utilized telemetry data collected from the MOBA Defense of the Ancients 2 (DotA 2), a game often compared with League of Legends, to characterize relationships between player behavior and ranking in MOBA games. The complexity of this game genre allows for a diverse set of approaches that can be taken towards the recorded data. In this case, the spatio-temporal data analyzed suggests that the behavior of teams is highly related to team skill, e.g., the closer to the professional tier players are, the more likely it is that they focus on staying as a grouped unit to conquer map objectives, while the lower a player is the more he/she values solo play.

K. Samperi *et al*. also analyzed player behavior by studying how often players respected real life social norms in virtual environments [22]. By analyzing the paths that player avatars used in the Second Life game environment (Figure 7), they noticed that despite there being no downside to stepping on the virtual grass, players avoided doing so, which suggests that personal conventions are unintentionally carried from the real world into virtual environments.

Figure 7 - Routes taken by avatars in 2010 on the Hyde Park region of the Second Life game map [22]

In behavior analysis, it is also important to go beyond spatial data, by adding a temporal component, as it can give additional relevant information, e.g., two players can perform the same set of actions in the exact same places but with different speeds, which can be interpreted as two different behaviors (one player being more careless than the other for example).

2.2 Visualization Techniques in Video Games

Visualization techniques have been used in the video game industry for a long time [6]. There exists a diversified number of ways in which these techniques can be used, but not every case takes full advantage of some techniques, or even applies them in the best way possible [6, 21, 23]. Understanding which techniques better fit certain types of data or user is an integral part of developing a good product. This means that before applying these techniques to analyze data, it is crucial to analyze the techniques themselves.

The use of visualization techniques is a common approach both inside and outside the context of video games. This work focuses on the techniques applied in the context of video games. Nevertheless, some of the research done in other areas is taken into consideration since, even though some of the issues may be unique to the context of video games, other challenges may be similar, or even perhaps, the same in other areas dealing with data analysis. Therefore, these contexts must also be explored to further understand how techniques in other areas can be adopted for the analysis of gameplay data.

2.2.1 Classification of Visualization Techniques

Most video games have been using simple representations, such as health bars and overhead maps for a long time. The type of game, and consequently, the type of data collected from the game determines what type of visualization technique must be employed [6]. Other factors, such as the target audience, play an important role in deciding which representations to use: if it is primarily targeted at the gamer community, these visualizations will fall under the topic of casual information visualization. On the other side of the spectrum, if the target audience is the development team, other visualization techniques may be more adequate [6].

Bowman *et al*. [6] defines a design space of visualization for games. This taxonomy focuses on components that are specific to both games and visualization technologies, hence, other issues, such as data type, utility and visual maps, are not considered. This framework consists of five main categories that can be used to classify any visualization technique found in computer games.

Primary Purpose

This category captures the purpose that made the visualization be created. It can take one of five possible values: Status, Training, Progression, Communication and Debugging and Balancing [6]. Status visualizations transmit important information to the player (typically continuously and in real time). Examples of this type are health bars and ammo counters (Figure 8).

Figure 8 - Health and ammo bars (left and righ) on the popular shooter Overwatch [1]

Training visualizations are devised to help players improve their gameplay. This is typically done using replay theaters (Figure 9), where players can watch their own gameplay and identify mistakes, or using visual overlays that can help, for instance, to identify optimal pathing deviation in racing games. Sometimes players are faced with different directions that can be taken to advance in a game and, it is increasingly more common to use visualization techniques to display these options. These representations fall into the category of Progression. Some examples are technology or class trees, present in many RPGs (Role Playing Games), or supply and demand bars in the game SimCity[2]. As mentioned before, in the recent years, it has become increasingly more popular to spectate other people's gameplay as a means of entertainment. Visualization

[1] https://playoverwatch.com/en-us/

[2] http://www.simcity.com/

techniques that fall into the Communication section are often used in these scenarios. Finally, Debugging/Balancing techniques are also employed by companies to help detect flaws and to balance gameplay for all types of players.

Figure 9 - League of Legends replay system [1]

Target Audience

This category represents who is the target audience of the visualization technique: Players, Developers or Observers [6]. The majority visualizations are targeted at Players, as they are the biggest group that interacts with video games. Optimal performance is not always the main purpose of these visualizations and they are often integrated in the game itself. Developers use techniques to analyze telemetry data for debugging, balancing and playtesting. The last group, the Observers, have slightly different needs than the Players and approaches such as highlight reels or animated maps are commonly used to meet their demands.

Temporal Usage

The temporal usage captures the timing aspect of a visualization's use. Most commonly there is continuous techniques. Traditional cases of this type of visualizations are healthbars and its variations, for example, ammo, power or mana bars, which are characterized by being constantly updated to provide live feedback, and are usually always visible by being integrated in a heads-up display. On the other hand, intermittent techniques are usually hidden and only come up upon being called due to their size or distracting qualities. Retrospective representations are used outside the game in a postmortem fashion, and allow the users to study their performance. Finally, there is

[1] http://na.leagueoflegends.com/en/news/client/client-features/road-pre-season-replays-horizon

Prospective representations that are designed to help the user make predictions about the future. A good example are color-coding techniques on the names of monsters in massively multiplayer online role-playing games to inform the user of the chances of success when battling the enemy.

Visual Complexity

The visual complexity classification captures the level of visual sophistication of a visualization technique, which can be Basic, Intermediate or Advanced. Basic representations are very simple and do not need an advanced degree of visual literacy from the user to understand them. The Intermediate techniques go a little further in complexity and use more advanced mappings that go beyond the standard. Some examples are statistical data graphics and in-game sprites for guidance. Lastly, Advanced techniques require advanced visual language and are more complex. Examples include choropleth maps and diplomacy maps.

Immersion/Integration

It is also important to capture whether the visualization is part of the game application or not and its immersion factor in the game. Visualizations implemented inside the game itself that go hand in hand with the game's atmosphere can be categorized as Immersive/Integrated. Informative/Integrated representations are also implemented inside the game but provide additional information about the game state that the player's character would otherwise have no access to inside the game world. Some visual representations can be Immersive/Separate which can allow for interaction with the game world from the outside world. Good examples of this are chat applications that allow players to participate in in-game item auctions using their smartphones. Finally, Informative/Separate techniques are very commonly deployed via the use of APIs to create applications that take advantage of in-game data to display information using various visualization techniques.

2.2.2 Current Directions and Common Techniques

As V. Zammitto mentioned [16], the gaming industry has still yet to grasp everything that visualization techniques can bring to game development and player experience. Certain techniques only work for specific game genres and others can be used across multiple ones. Some are yet to be explored and employed in the context of video games. The current directions, as well as common visualization techniques being applied in spatial game analytics and visualization are outlined below.

Some of the most common visualization techniques employed in the video game industry today can vary from simple graphs and charts (Figure 10), to more complex 2D and 3D maps (Figure 11).

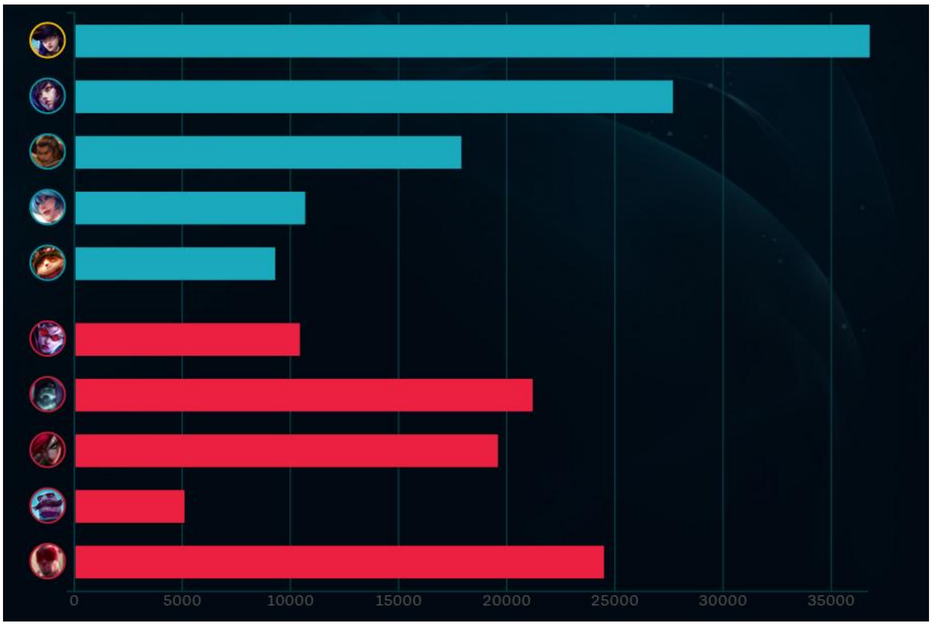

Figure 10 - Graph in the post-game lobby of a LoL match with the total damage dealt by each player[1]

Because of their simplicity and effectiveness, when applied correctly, graphs, tables and diagrams are some of the most frequently used techniques in the context of video games [5]. Nevertheless, these techniques do not normally allow for spatial analysis, such as trajectory analysis, whereby, visualization techniques that combine the use of a map with the available information, offer a much richer context that a non-spatial analysis will not provide, therefore enhancing the analysis [13].

Figure 11 - League of Legends overhead map of Summoner's Rift[2]

One of the simplest approaches to represent data in a map consists in the use of points and/or lines over a geographic area to construct a static map, where each point

[1] https://www.leagueoflegends.com
[2] http://imgur.com/mAYo45a

symbolizes a visited location [18]. Other events or information can also be represented using various techniques that may involve the use of different symbols and colors (Figure 12) to easily convey meaning [5, 7, 23]. Some visual properties like color cycling or path thickness can also improve these visualizations by highlighting the temporal component of movement [5]. Choosing the right visual properties to use may be challenging, since some of them are more adequate to represent certain types of data than others, e.g., color hue is typically better suited to represent different categories, while color value is commonly used to transmit the meaning of order [24].

Figure 12 - World of Warcraft map with information about the distribution of enemies[1]

Choropleth maps are another example of a simple approach in which areas of the map are shaded or patterned in proportion to the measurement of the statistical variable being displayed [6]. This technique is widely used in real world applications, for instance, to demonstrate the distribution of life expectancy (Figure 13) for all the countries. In the context of video games, this technique has been used inside the game environment in genres such as CMS (Construction and Management Simulation) and LS (Life Simulation). In these genres, players must have access to the distribution of certain statistical variables, along the virtual playing field, to be able to make decisions that impact their gameplay positively, according to their objectives.

[1] http://www.wowlevelinguide.com/wow-leveling-map/

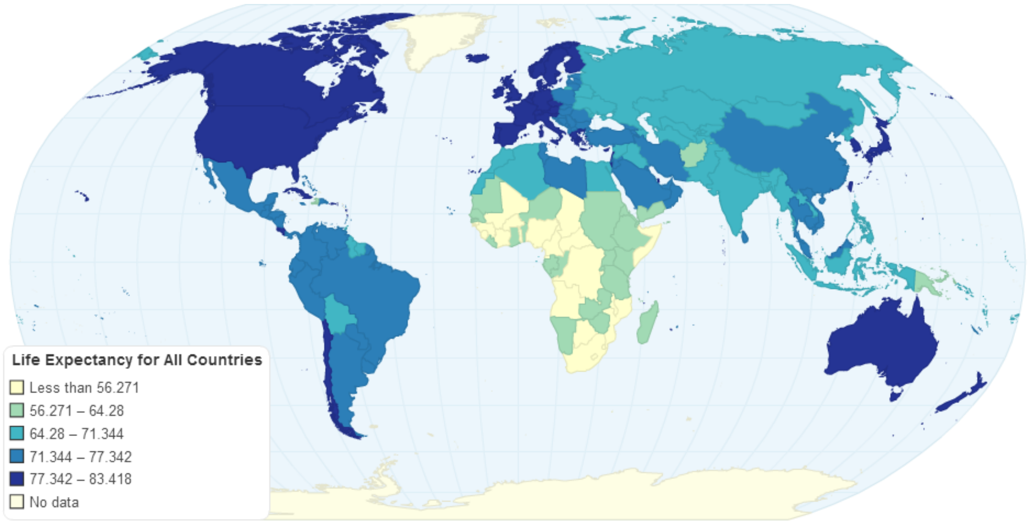

Figure 13 - Choropleth map with life expectancy for all countries

Figure 14 demonstrates an example of this technique, applied in the context of video games. This map represents crime distribution in one of the cities of the popular game SimCity[1]. This choropleth map is supplemented with other visualizations, such as bar charts and icons, that represent the distribution of criminals and points of interest respectively. The different tones of blue used demonstrate the distribution of police across the visible area, with darker tones representing higher police presence and lighter tones representing lower police presence. An analysis of this map allows players to make decisions regarding which areas of the map are more dangerous and, consequently, which areas need higher police presence.

Figure 14 - Choropleth map from the game SimCity[2]

[1] http://www.simcity.com/

[2] https://i.imgur.com/PWlXqeB.jpg

Heatmaps are another two-dimensional representation of data in which values are represented by colors overlaid in a map [18, 25]. To generate these, maps are divided under scrutiny into a grid of cells and the events that fall in each cell are used to calculate that cell's value [13]. Regardless of how easy their creation is, heatmaps require a large amount of data to be useful and can sometimes conceal important information due to design restrictions [5], e.g., a 3D environment being mapped to a 2D heatmap may need to forgo some information such as height. Heatmaps are considered to be very easy to analyze and can provide various types of insights from any variety of data, e.g., analyzing a heatmap that shows the distribution of player's deaths over a certain area can be useful not only to understand where players die the most, but also what is the impact of different enemies or weapons in different regions of that area [13].

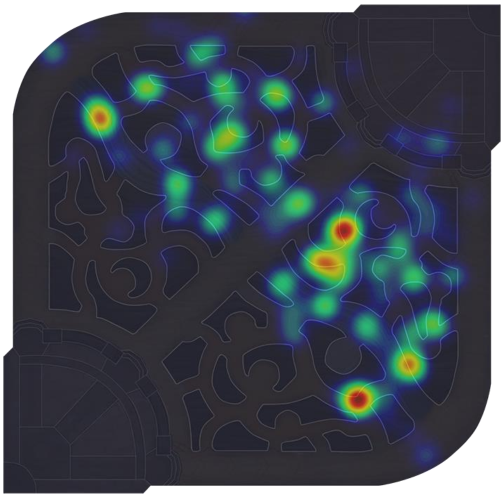

Figure 15 – 2015 LoL World Championship heatmap example[1]

Figure 15 represents a heatmap based on the League of Legends map (Summoner's Rift), where the location of scouting units (known as wards) placed by a team during the 2015 World Championship is shown. The analysis of this visualization technique can provide insights into which areas of the map are more prone to be contested in terms of vision control. It can also be used to understand if certain teams have a tendency to focus on some specific zone or objective. Furthermore, this visualization can be used by casual players that want to learn which areas of the map they should focus on controlling more often to improve their performance. These maps can also be used to provide insights into why certain areas of the map are not being used [13], which can help developers balance gameplay to prevent unfair advantages to certain players.

[1] http://na.leagueoflegends.com/en/page/heating-how-pros-warded-worlds

Figure 16 - CS: GO heatmap example[1]

Figure 16 is another example of the use of heatmaps that shows firing locations for each type of weapon during the beta test of a map of the popular FPS game Counter-Strike: Global Offensive (CS: GO). This approach can be used to understand exactly what areas of the map are not being used and why, e.g., maybe a location is not too favorable to fire from because of the lack of visibility.

The problem of these static map approaches is that they do not allow for a temporal analysis of the data, i.e., it is not possible to analyze the variation of the metric being mapped over time. By adding the temporal dimension, it would be possible to filter information according to specific time intervals to study what happened during different periods of the game. It would also be possible to visualize the evolution of the metric over time, which in turn can enrich the analysis and lead to different, more detailed results. For instance, by analyzing the map in Figure 15, one can only understand which areas of the map were most important in terms of vision control during that match. If the temporal component was added, players could visualize how the areas of focus for this

[1] http://blog.counter-strike.net/science/maps.html

metric varied throughout the game, which can help players understand which zones should be the focus in the earlier stages of the game, and which zones should be focused later in the game.

One interesting approach to map visualization, that combines the use of the temporal dimension, is the Spatial-Temporal Cube (STC). The STC (Figure 17) is a visualization technique that represents both spatial and temporal information within a cube, where the *x-y* axes usually represent spatial information (e.g., latitude/longitude), while the *z*-axis represents time [26]. Typically, time increases along the *z*-axis indicating that the higher the information is within the cube, the most recent it is.

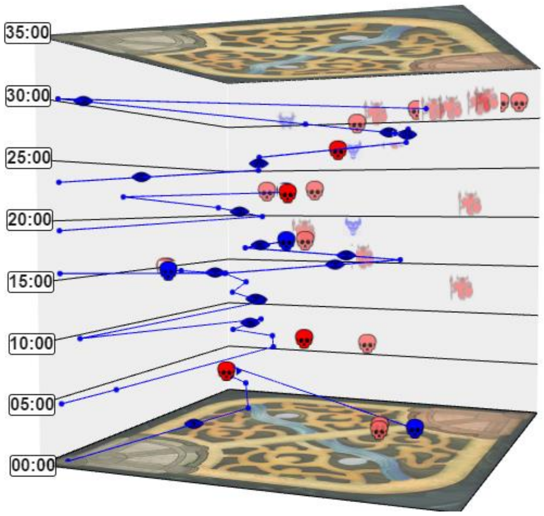

Figure 17 - STC of the VisLoL application [18]

This technique has the advantage of presenting a continuous change in time and space, which improves the perception of movement, even when unexpected changes occur [27]. Similarly to static maps, this technique also allows for the incorporation of visual attributes to convey thematic information, as can be seen in Figure 17, where skull symbols denotate a player's time and place of death. The main aspect that this technique brings to the table, is the integration of the time component with space variables in a single representation, which creates a richer visualization that allows users to evaluate the changes in position of players over time. Consequently, this allows users to understand the impact that the observed actions have in the performance of the players [18]. However, due to their 3D characteristics, the interaction with the STCs can be affected by human perceptual limitations which can cause confusion while using this technique [28]. To minimize these problems, previous studies suggested the use of interactive features, such as changing the point of view within the cube [29] or moving the plane representing spatial information up/downwards, to facilitate locating objects in space and time [30].

The animated map is a technique that also combines the spatial and temporal components of data to allow singular images to be reproduced in sequence, supporting the analysis of the variation of player and event location over time [18]. Animated maps display, automatically, a sequence of maps (frames), usually, in a single view, and take advantage of the computer's capability to rapidly update its contents. These maps have been proposed as an ideal method for learning and scientific discovery because they can explicitly represent dynamic systems and processes [31]. Furthermore, the results of previous studies present in the literature suggest that animated maps allow for more rapid interpretation of spatio-temporal information than do static maps [32].

Map animations can be sub-divided into spatial and temporal animations. Spatial animations are used to demonstrate changes of attributes of a dynamic phenomenon, with no direct relation with world time, such as a change in perspective (Figure 18). On the other hand, temporal animations describe variations on the map following a chronological order (Figure 19), which imply the existence of a direct relation between displayed time and world time [33].

Figure 18 - Spatial animated map that shows change in perspective[1]

Studies show that animated displays can help reveal spatio-temporal patterns that are not evident with common static representations [34]. Some studies state that animated maps have the potential to be used either for representation of exploration purposes [35]. For representation purposes, animations should be simple enough to properly convey the intended message. For exploration purposes, it is necessary to provide tools that allow the visualization of the spatio-temporal properties of the data in different ways (e.g., different levels of zoom in the map).

[1] https://www.mapbox.com/blog/perspective-maps-in-mapbox-studio/

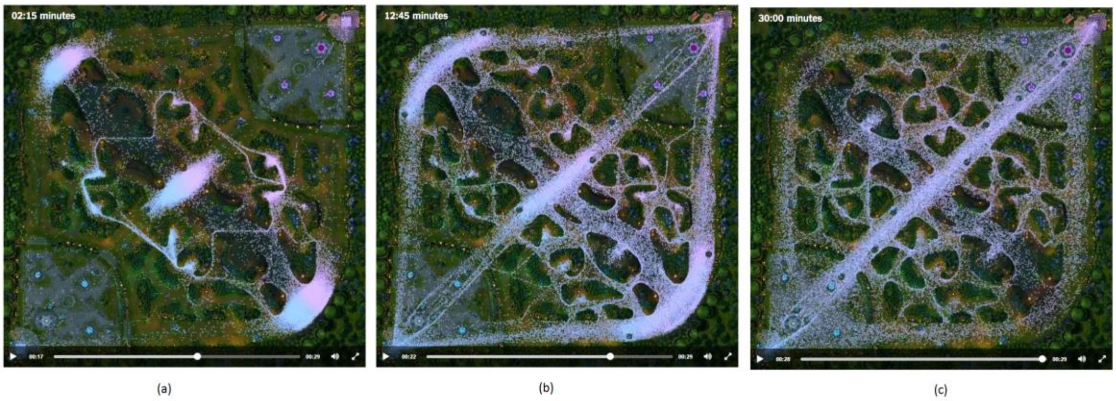

Figure 19 - Temporal animated League of Legends map with data from 10.000 matches regarding players position at three different times after the game started: (a) 2:15, (b) 12:45 and (c) 30:00[1]

Andrienko *et al.* [36] identified three variants of animated representations of the movement of objects: snapshot in time, movement history, and time window In the first variant, each map frame only shows the current positions of the objects corresponding to the moment being displayed. In movement history, the routes the objects take from the starting position to the current position are displayed. Consequently, at the end of the animation, the entire routes that the objects travelled will be displayed. The time window variant follows an approach situated between the other two, by having the map show fragments of the routes made during the time interval of a specified duration. The authors also argue that the variant snapshot in time is more suitable for the exploration of the movements of a single object, whereas the variant movement history helps preventing the analysts from losing track of the objects. Lastly, they argue that the last variant is the most convenient for the exploration of object behavior, in terms of speed of movement.

Unlike static approaches, animated maps have an additional dimension that can be used to present information. Consequently, visual variables, similarly to the ones used in STCs, can be applied to represent thematic attributes. However, the amount of data presented increases with the duration of the animation. Furthermore, representing thematic attributes in zones where multiple events occur simultaneously can cause clutter that creates difficulties when analyzing the displayed information. In addition to that, the fact that a frame will not always be visible on the display, may raise some cognitive and perceptual limitations, since the longer the animation lasts the less likely the users are to memorize all relevant information [37]. Therefore, it might be necessary to use approaches that aggregate the information being displayed in the map to prevent the visualization from becoming confusing or obtrusive due to the high amount of data being simultaneously displayed.

[1] http://www.nytimes.com/interactive/2014/10/10/technology/league-of-legends-graphic.html

Several animation parameters can be used to help the representation and exploration of information. These include, among others: speed, moments/intervals, and direction of animation [36]. Events can also be filtered to improve the analysis when using animated maps. This can lead to less visual clutter which results in a reduced cognitive effort for the analysts.

This technique has the major advantage of revealing spatio-temporal patterns that other visualizations hide [34]. Furthermore, in the context of video games, this technique makes it possible to create a simplified simulation of a match from any game. This can be useful to analyze matches where the position of players impacts their performance. MOBA is an example of a type of game which can benefit from this technique. In this genre, it is not sufficient to know that an event took place in a certain location, it is also important to visualize the position of the participants in relation to that event to correctly analyze their performance.

Multiple features and techniques can be combined during visualization analysis so that insights regarding how they influence each other can be gathered. Combining player trajectories with the locations of their deaths can provide a highly detailed analysis of the dynamics of a playfield in a FPS game [13]. One technique that can be employed to achieve this effect is overlapping, in which two or more maps or layers are registered in a common coordinate system being superimposed on top of each other [9, 10]. The overlay function can be based on simple operations, such as synthesis (showing trajectories combined with the location where players die) or analysis (subtracting death heatmap from a kill heatmap to understand what zones are more dangerous).

In Figure 20 an example of overlay analysis can be observed, in which a balance map was generated using an overlay function that subtracted a death heatmap from a kill heatmap [13, 38]. This view of the data permits to highlight the dangerous places in the map. Zones with negative value (shown in red) indicate dangerous areas, while zones with positive values (shown in blue) indicate areas that are safer. In the context of this example, this leads to the conclusion that centers of hallways are much safer than the large, open areas in the center of the map. Walls in general seem to be very dangerous, most likely because player movement is restricted and it is much easier to get hit with splash damage.

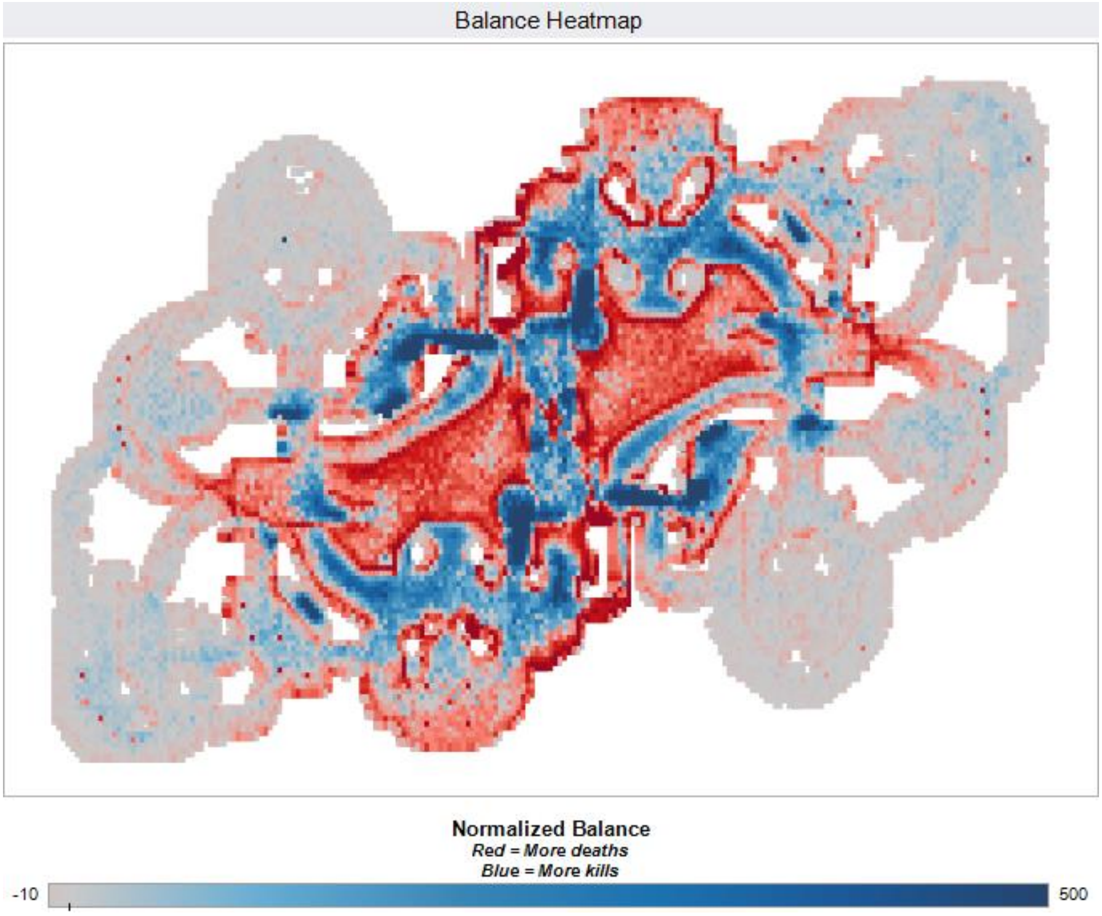

Figure 20 - Overlay analysis of the "Molten" map of the game Transformers: War of Cybertron[1]

2.2.3 Comparative Approaches

Comparative visualizations can be of interest for various groups in the context of game applications [7]. Developers can assess their game regarding the consequences of design decisions by using telemetry data. Visualizations can help to uncover issues that can subsequently be solved to tailor the game to the different needs of the various groups of players. Players and spectators can use comparative visualizations to monitor and compare the progress of other individuals. Players can also use these techniques to track their progress and to study how they are performing in comparison to their peers.

There are three basic approaches for comparative visualization: juxtaposition, superposition and explicit encoding [7]. Juxtaposition displays each visualization separately in their own view. This type of representation is most useful for exploring and comparing differences and similarities. It is also the most common because of its flexibility and ease of implementation. Small multiples are a common example of space juxtaposition (Figure 21). This technique consists of the consecutive juxtaposition of several (static) maps in the same display [19]. Each single map represents the state of a

[1] http://www.gamasutra.com/view/news/125213/Opinion_Balance_and_Flow_Maps.php

phenomenon at a different moment in time. When considered as a whole, these maps make up an entire event [39].

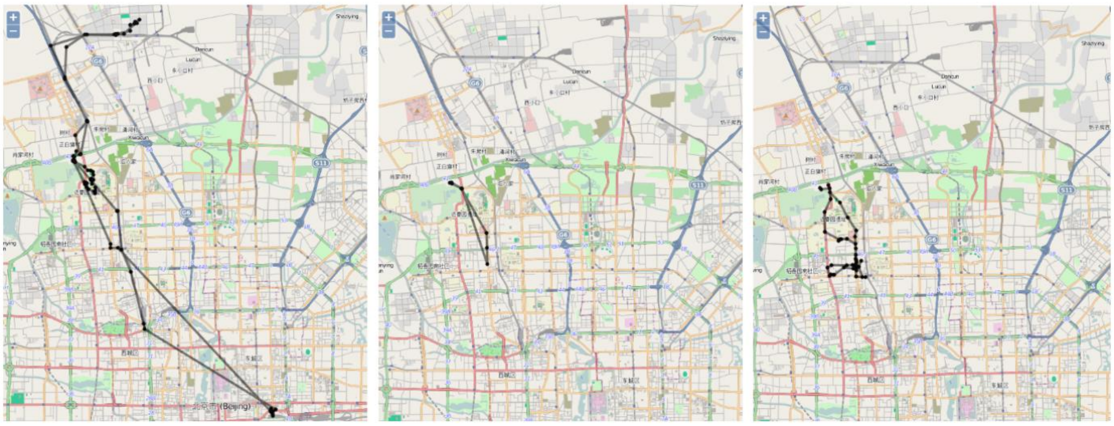

Figure 21 - Example of a small multiples map visualization. In this example, each map represents one day of movement [19]

Animation, i.e., a sequence of visualizations that change in chronological order, can be considered as juxtaposition in time (Figure 19), according to Gleicher *et al.* [40], if "*it predominantly requires the use of the viewer's memory and attention shifts to make connections between objects*".

As opposed to juxtaposition, superposition visualizes different data sets in a way that they share the same visual space, usually by overlapping or alternating the visualizations on top of each other [7]. This can be achieved using different colors for each dimension that is being represented. It has advantages when compared to the previous approach because it makes it easier to understand the visualizations in the context of each other and can be beneficial for the user since it does not require him/her to split his/her attention between more than one view. However, it can lead to visual clutter or can occlude interesting information.

Finally, the explicit encoding approach visualizes the relationships between the different data sets in a dedicated visualization to help users detect differences, correlations or similarities [7]. As opposed to the two previous approaches, this one can minimize the viewer's effort by providing a visual encoding that allows the relationship between the data sets to be clearly and easily discerned by the user. The differences between these approaches can be seen in Figure 22. These maps were generated from replay data from a StarCraft 2[1] match between two players. Yellow tones represent the death location of units from the first player whereas red tones represent the death location of units from the second player.

1 http://us.battle.net/sc2/en/

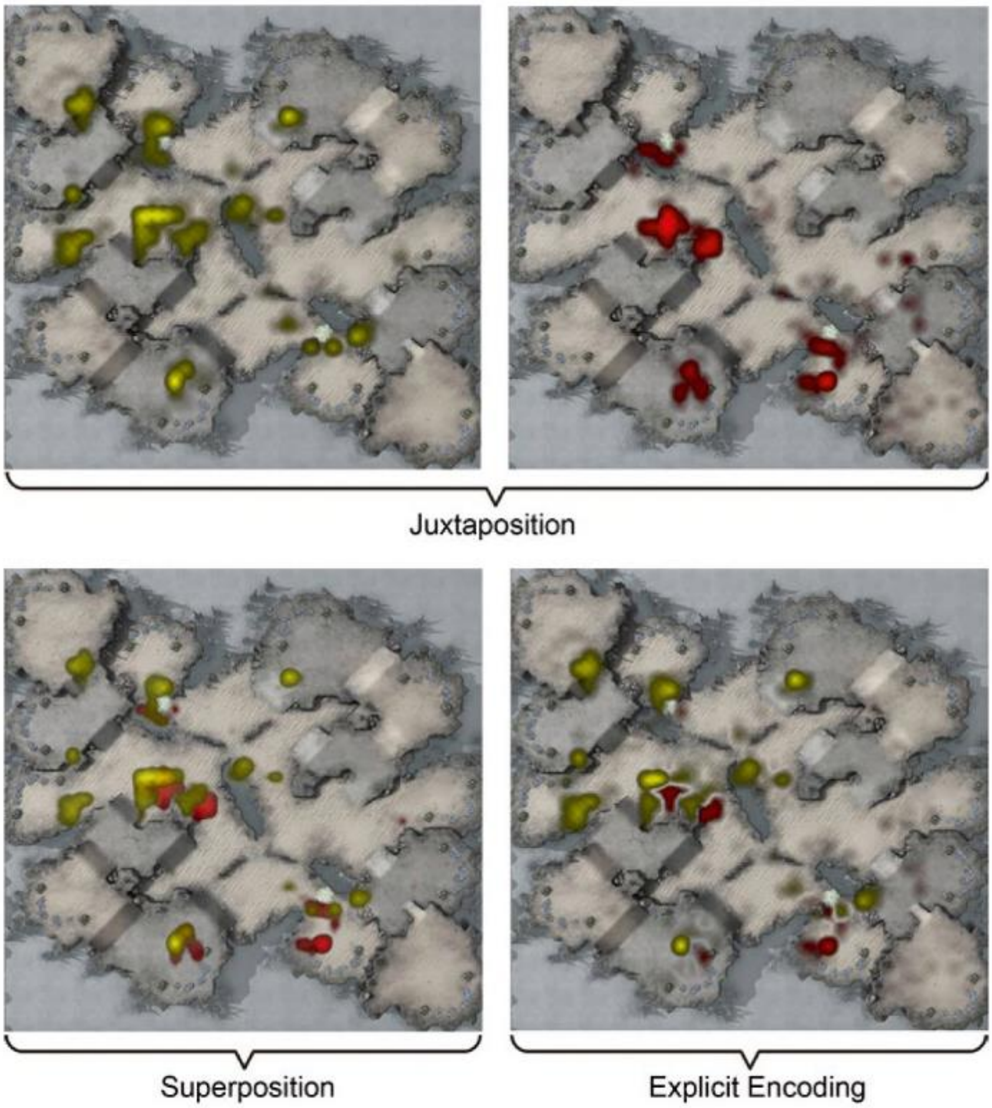

Figure 22 - Three basic approaches for comparative visualization illustrated using heatmaps [7]

2.3 Discussion

The review of related work yielded interesting conclusions. First, there is a large number of visualization techniques that have the potential to improve the current state of visualization in games. Although many might not be applied in the most adequate way, or be applied at all, namely animated maps, studies show that there is an increased interest in exploring and analyzing data related to games using these techniques. Most of the techniques applied in this context are based on graphs tables and static maps. These techniques, however simple and useful, do not typically allow for more complex analysis.

Secondly, the increase in popularity of online video games created a constant source of player-derived telemetry data that can be used to apply visualization techniques. In turn, this also raised the attention of groups interested in video games that now want to take advantage of these techniques to analyze data for their own benefit. The complex nature of modern games translates directly into a complex set of data that can be extracted from them. This complexity should be addressed by studying which visualization techniques are better suited for different types of data, that at the same time meet the expectations of users. Only this way can stakeholders extract relevant conclusions and patterns from the exercise of analysis.

The analysis of the state of the art reveals that, to the best of our knowledge, there is no case in the context of video game analysis where the use of animated maps was studied. The ease of use of this technique, alongside its adequacy to represent and analyze spatio-temporal data, seems to point out to the hypothesis that this technique can be a welcome addition to the field of game analytics, more specifically, the analysis of player performance. Furthermore, this technique allows users to visualize a simulation of a match which can be used to extract relevant patterns of gameplay. Lastly, because this technique incorporates both the spatial and temporal components of the data, it allows users to perform various types of analysis, namely trajectory analysis, that can help them create relationships between the locations and trajectories of players and the game events, which can enhance player performance analysis. Consequently, the work developed will focus on representing spatio-temporal information with the purpose of analyzing player performance using animated maps.

Chapter 3

VisuaLeague

The analysis of the state of the art of visual techniques applied to video games shows that there exists a substantial interest by various groups in analyzing video game data. However, many of the known techniques remain unexplored in this context, especially regarding spatio-temporal data.

This chapter focuses on the description of the developed prototype, VisuaLeague. This prototype aims at adopting an innovative approach, using animated maps, to allow users to analyze the performance of players in matches of the game League of Legends, in a post-mortem fashion. A description of the game as well as the telemetry data captured from it will be presented first (Section 3.1), followed by a breakdown of some well-known applications designed for player performance analysis (Section 3.2). Lastly, the design and implementation of the prototype will be presented, accompanied by its features and limitations.

3.1 League of Legends and Telemetry Data

3.1.1 Game Description

One of the main propellers of *e-sports* has been Riot Games with the online video game League of Legends (LoL). Since its release, Multiplayer Online Battle Arena (MOBA) games have become the most played online games since the surge of Massively Multiplayer Online Games (MMOGs) [41]. This subgenre of video games is characterized by being played by two teams, typically with five elements each, that launch coordinated attacks on each other's base in order to destroy it (Figure 23) [18, 41, 42]. Matches can last indefinitely, although they usually tend to last between 30 and 40 minutes. The match duration is typically divided into three important periods: early-game (up to 10-15 minutes), mid-game (up to 25-30 minutes) and late-game (until the end of the game).

Each player, referred to as a summoner, can choose a character, commonly known as a "hero" or "champion", from a roster with already over one hundred possibilities and continuously increasing[1]. Every champion features a unique set of abilities which can be used to interact with other players and the virtual world.

Figure 23 - Example of gameplay in LoL[2]

A match takes place in a squared map composed of three main lanes (commonly known as top, mid and bottom) that connect both team's bases which are located in opposite sides of the map (Figure 24). Between these lanes, exists a zone called jungle, inhabited by monsters that spawn periodically in fixed locations. When slain, these monsters grant monetary units (gold), experience points (XP) and other rewards that permanently or temporarily improve the abilities of champions. Experience points allow players to level up their champions improving their combat capabilities and allowing them to learn new skills that unlock new ways of interacting with the virtual world and other players. Gold can be used to purchase items from the corresponding player's base that enhance the battling capabilities of the player's character.

Along the lanes there are multiple defensive structures called towers (nice in total for each team, three per lane and per team) that protect each base. All the towers in a lane must be destroyed before players can infiltrate the enemy base through the entrance located in that lane. Inside each base, there are three structures called inhibitors and one called nexus. At least one inhibitor must be destroyed for a team to be able to attack the enemy nexus. The team that destroys the enemy nexus first is considered the victor.

[1] http://gameinfo.euw.leagueoflegends.com/en/game-info/champions/

[2] https://www.leagueoflegends.com

After the 20th minute mark, any team can surrender by having a voting session. If at least four out of the five players on that team approve this decision, the game ends and the enemy team is considered victorious.

Periodically, in each base, relatively weak computer controlled units (called minions or creeps) spawn and travel down each lane in the direction of the enemy base. When killed, these units grant XP to nearby champions and gold to the killer. When an inhibitor is destroyed, the minions of the team that destroyed this structure spawning in the lane where this inhibitor is located, are significantly empowered during a period of five minutes, and can serve to pressure the enemy team to actively defend their base. After this period, the inhibitor regains all its health and the minions' stats return to their normal values.

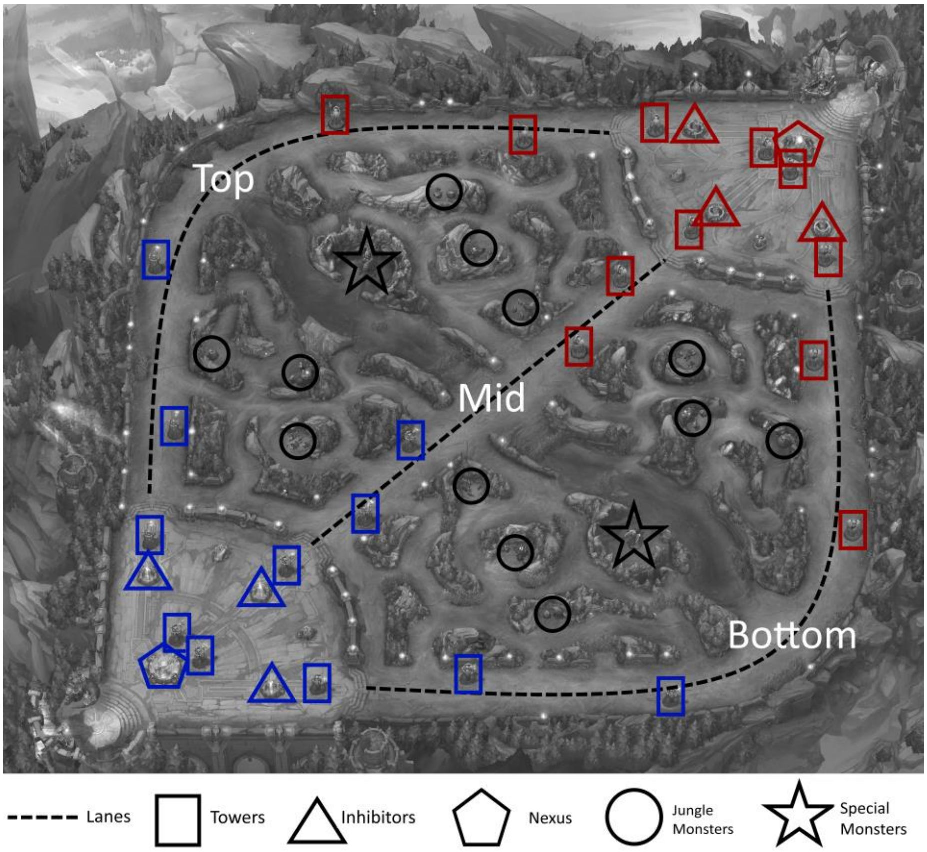

Figure 24 - League of Legends map[1]

There are also, spread across the map, multiple objectives in the form of special monsters (dragon, baron, rift herald and rift scuttler) that, when slain, provide rewards to the team that conquered them. These rewards help players get stronger and facilitate reaching the win condition.

[1] https://i.imgur.com/HRgupVM.jpg

Each player starts the game with the chosen champion at level one, and can level it up to eighteen, which improves its abilities and stats. This process can be done by interacting with other players and the entities referred above. Normally, each player fills a specific role in the team: one player goes to the top lane (Top) and another to the mid (Mid), two players go to the bottom lane (Attack Damage Carry (ADC) and Support) and the remaining player goes to the jungle (Jungler) [42, 43]. The Top and Mid roles tend to have an isolated playstyle when compared to the other roles. Usually, being able to create advantages by themselves when compared to these players' direct opponents is very valued in these positions. Furthermore, being able to turn their advantages into ways of helping their teammates is also considered a mark of a good player. The ADC and Support roles are usually played in collaboration, hence synergy between the two is important. The ADC role is typically filled by champions who can output a sustained amount of damage over time, making this the role's primary focus. The Support role however, tends to be filled by champions that can aid their ADC with supportive skills that turn him/her stronger, although many other strategies are also considered viable. Support is also the main role responsible by controlling vision around the map, despite other teammates helping with this task as well. Lastly, the Jungler is responsible for ambushes (ganking), which means he fills a position that moves around the map, visiting the various lanes to try and help his teammates get ahead by killing the enemy players or taking objectives. Because the player filling this role moves around the map frequently, it is commonly considered a secondary controller of vision.

Players can temporarily eliminate any adversary by reducing their champion's health points to zero. The player that executes the last blow on the enemy champion is awarded a kill and the player being slain is attributed a death. Other players that contributed to the death of the adversary (by damaging or using abilities) are rewarded with an assist. The player that was killed will respawn after a small period depending on his current level and the current duration of the match. This event awards the players that eliminated the enemy with gold and XP. Players usually organize themselves as a group, and fight each other in a coordinate manner to contest the various objectives around the map. This behavior is commonly described as team fighting.

Fog of War[1] is an extremely important aspect of the game. This concept, borrowed from the military vocabulary, refers to the uncertainty in situational awareness experienced by participants in military operations. In LoL, this concept is applied by having characters' vision limited to a certain range, from which they can no longer perceive what is happening (Figure 25). Mechanics like this create room for strategy development around vision and zone control which leads to player's location and

[1] https://en.wikipedia.org/wiki/Fog_of_war

movement requiring careful planning to facilitate the win condition. In-game items called wards can be purchased by players and, when used, serve as temporary stationary sentinels that grant vision of an area to the team that places them.

Figure 25 - Fog of War example

The complexity of modern video games, results in a very large and complex data set that can be collected from them which, when analyzed, can yield very interesting results. As can be seen by the description above, League of Legends fits this description. For this reason, and because of the massive success of the game, the Riot Games API will be used as a source of player-derived telemetry data from League of Legends matches. This data set will be used by the prototype that will be described in the following sections. Spatio-temporal components of this data are of special interest as they can be utilized to analyze strategies for vision and zone control, as well as obtaining insights into player performance. The following section describes in detail the data available via this API.

3.1.2 League of Legends Telemetry Data

A large amount of information regarding each match is provided through the Riot Games API. This section describes in detail the spatio-temporal and thematic data available via this API. The data mentioned can be accessed via web services and is provided in JSON format.

Each file describing a match contains a list with static thematic information about each player during the match. This information was partially used in the development of the prototype but, since it was not the focus of this work, only a brief description will be made available. The information contained in this part is mainly focused in three areas: pre-match information, post-match statistics and social information. The first refers to choices made by the player before the match started that cannot be changed during its course. This data relates to choices in different combinations of pre-match game mechanics called runes and masteries that have effects on the combat status of the chosen champion. There is also information available about abilities called summoner spells that the player can choose prior to the start of the game and can aid him/her in combat. The second part of the data refers to statistics about the match and its participants. These statistics inform, for example, about the total damage dealt or the number of wards placed for each player during that match. There are also summary fields present in the data, that represent variations of in-game thematic values, such as gold and XP, during fixed intervals of time. These fields are detailed in Table 1.

Table 1 - Summary fields

Name	Description	Example
xpPerMinDeltas	Experience gained per minute	306.1
goldPerMinDeltas	Gold gained per minute	224.8
creepsPerMinDeltas	Creeps killed per minute	6.2
damageTakenPerMinDeltas	Damage taken per minute	300.6
xpDiffPerMinDeltas	Experience difference per minute	-59.74
csDiffPerMinDeltas	Creep score difference per minute	-0.44
damageTakenDiffPerMinDeltas	Damage taken difference per minute	71.04

The fields with "Diff" in their names represent the difference between the fields with similar names from players occupying the same role in opposing teams, e.g., `xpDiffPerMinDeltas` for a specific player represents that player's `xpPerMinDeltas` minus the value of his lane opponent's `xpPerMinDeltas`. Although these values have a temporal nature, upon further investigation, it was concluded that they are not of interest to analyze as they represent aggregated data over time, e.g., from 0 to 10 minutes, which can also be extracted in more detail through other fields described below. Finally, the social aspect of this data offers information regarding the highest rank achieved by players during the current competitive season.

The segment of data that was primarily used during the development of the prototype is a field called timeline that contains a list of frames. Each frame has a list of the events that happened since the previous frame took place. The duration of each frame is roughly 60000ms (1 minute) and it is accompanied by a timestamp that signifies when the frame was recorded. Each frame provides information regarding each participant's position and the value of thematic information, such as gold and minions killed, up until the time the frame was recorded. Table 2 and Table 3 describe the information present in the fields mentioned above. Because the API only provides information about competitive games, and the vast majority of matches (including all professional matches) are played in the Summoner's Rift map, only relevant information to the analysis of matches that respect these criteria will be discussed.

Table 2 - Event information

Name	Description	Example
eventType	Event type	CHAMPION_KILL
timestamp	When the event occurred (in ms)	4248

Table 3 - Player information

Name	Description	Example
currentGold	Participant's current gold	339
position	Participant's position	x: 7430, y: 6956
minionsKilled	Number of minions killed	15
level	Participant's current level	3
jungleMinionsKilled	Number of jungle monsters killed	1
totalGold	Participant's total gold	839
participantId	Participant ID	3
xp	Experience earned by participant	734

The information about a player's position is present in the form of coordinates (x, y) that represent longitude and latitude in the map. The event information is accompanied with extra data depending on the value of the field `eventType`, e.g., if `eventType` has the value ITEM_PURCHASED then information regarding the player who bought it (`participantId`) and which item was bought (`itemId`) is also available. The relevant event types and the respective information are listed in Table 4.

Table 4 - Event types and extra data fields

Event Type	Description	Extra Fields
BUILDING_KILL	Building destroyed	killerId, assistingParticipantIds, buildingType, towerType, teamId, position
CHAMPION_KILL	Player killed	victimId, killerId, assistingParticipantIds, position
ELITE_MONSTER_KILL	Special monster slain	monsterType, monsterSubType, killerId, position
ITEM_DESTROYED	Item destroyed	itemId, participantId
ITEM_PURCHASED	Item bought	itemId, participantId
ITEM_SOLD	Item sold	itemId, participantId
ITEM_UNDO	Item purchase undone	itemBefore, participantId, itemAfter
SKILL_LEVEL_UP	Skill level up	levelUpType, participantId, skillSlot
WARD_KILL	Ward destroyed	killerId, wardType
WARD_PLACED	Ward used	creatorId, wardType

These events have a spatio-temporal component associated in the context of the game, even though, some of them do not have explicit information provided via the API. In the case of events related with the placement of destruction of wards, the main reason for this lack of information is to prevent exhaustive analysis on the playing patterns of individual players, which might lead to an unfair advantage. Other events, such as those related to items, do not have this information because they can only occur at the current location of the player or at specific locations on the map, hence not needing the information to be explicitly provided. The only event that does not have a spatial component associated, is the leveling of skills but, due to its importance to understand the capabilities of different champions during a match, it was used nonetheless. Lastly, there's a field that represents how long the match lasted in milliseconds.

3.2 Analysis of Existing Applications

To understand what visualization techniques are currently being employed in the context of community dedicated platforms for player performance analysis in LoL matches, three of the most used applications were analyzed: LoLKing[1], OP.GG[2], and the official Match History web application[3]. A brief analysis of the replay system developed by Riot Games was also conducted. These applications use the visualization techniques previously described in Chapter 2, such as simple diagrams, graphs, plots and lists, to show a summary of statistical data regarding player performance during a match, e.g., number of kills/deaths, gold earned and items bought. Figure 26 shows some of these elements.

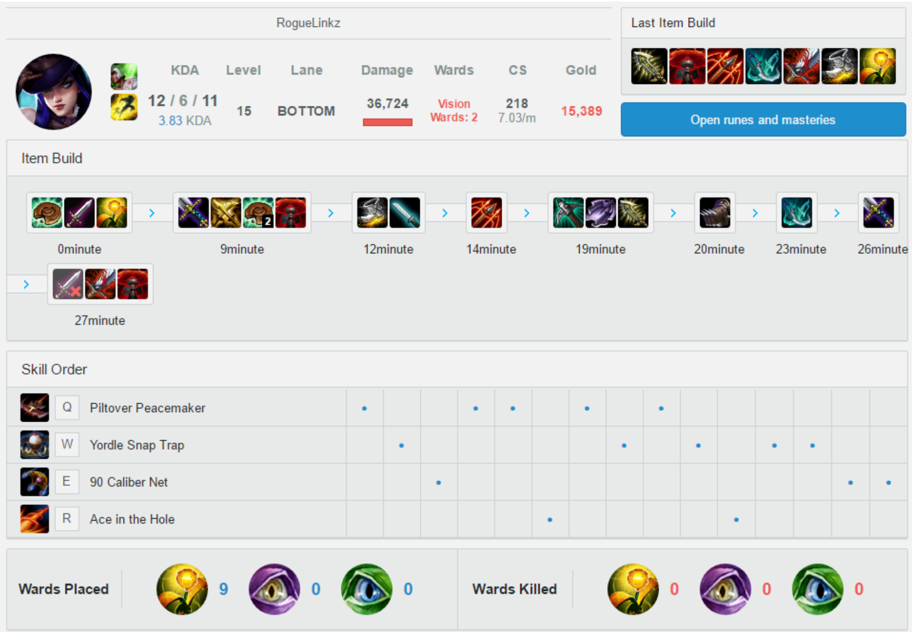

Figure 26 - OP.GG's summary of data regarding player performance[2]

As can be observed, most of the applied techniques simply offer information about end game statistics and do not allow for a more deeper and richer analysis because, for instance, they do not incorporate the temporal component of the data. However, two of the visualizations used in Figure 26 consider this aspect of the collected information. The Item Build section allows users to understand the order by which items were

1 http://www.lolking.net/
2 http://euw.op.gg/
3 http://matchhistory.euw.leagueoflegends.com/

bought by that player, which can help them decide not only what items to buy, but also when and in what order. In of itself, this supports a more complex analysis than the simple view of the final set of items the player ended the game with. The section regarding skill order conveys information related to the order that abilities were learned by that player throughout the match, which incorporates the temporal aspect present in the data as well. This allows users to analyze what skills are more important to learn first when facing certain opponents.

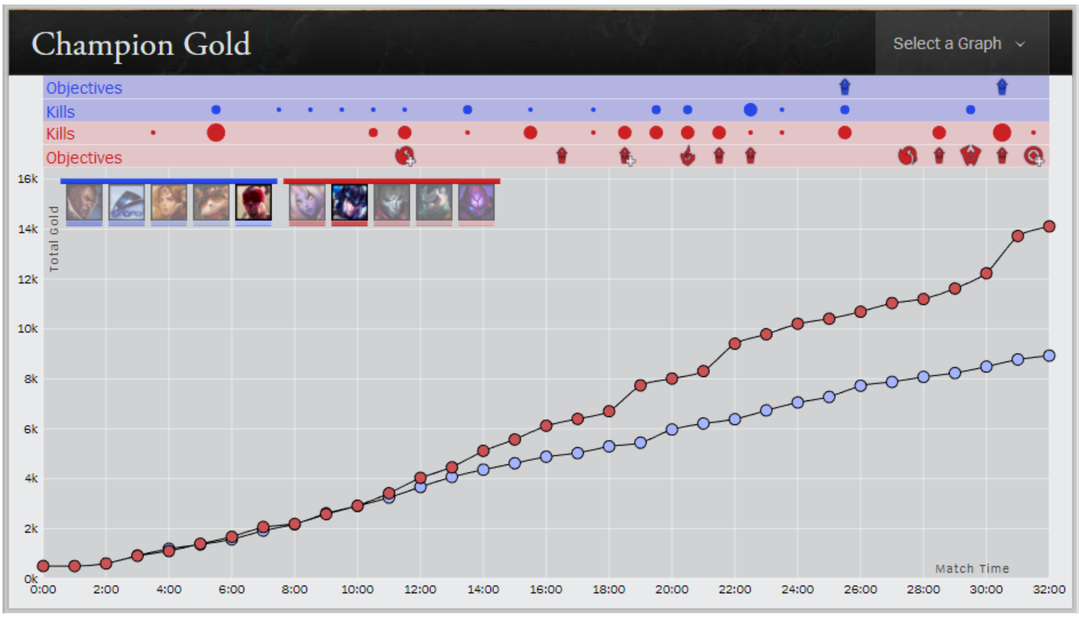

Figure 27 - Match History champion gold over time plot[1]

Most of these platforms feature graphs that show the evolution over time of in-game thematic information, such as gold, XP or minions killed (Figure 27). Although these techniques only allow a simple analysis, they can be combined to provide insights that aid in the evaluation of player performance. These platforms also allow to explore this data from the point of view of other participants of the match by changing which player is selected, typically by clicking on the corresponding avatar for the champion being played (Figure 27).

The analysis of multiple games to extract patterns and aggregate statistical data is also performed to inform the player of his/her evolution and current performance on various aspects. Figure 28 shows an example of the result of that aggregation regarding individual performance of a player on his most frequently played champions.

[1] http://matchhistory.euw.leagueoflegends.com/

Figure 28 – Performance data for most frequently played champions[1]

This type of analysis is also done on some of these platforms across games of multiple players in different rankings so that users can compare their performance with their peers. This data is usually shown regarding a champion or position occupied by a player during a match in a certain ranking range (Figure 29).

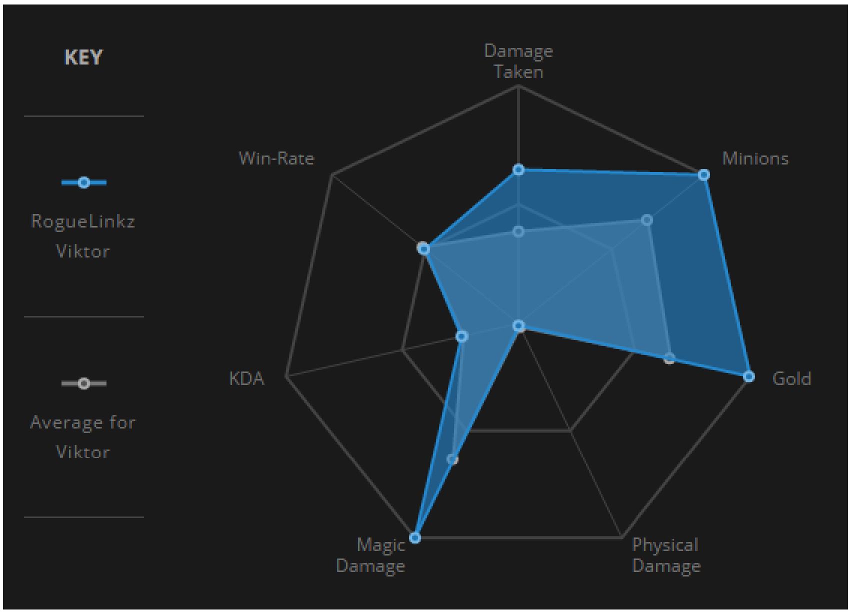

Figure 29 - LoLKing's radar chart for champion performance analysis[2]

Some platforms, such as LoLKing, attempt to calculate the variation of the performance of a player over time, based on his/her position in the ranking system and on the outcome of his/her matches. This is shown using a plot that features the Elo ranking value of a player as a function of time (Figure 30). This system is a method for calculating the relative skill level of players in competitor-versus-competitor games, such as chess. Although the Elo ranking system is not officially used anymore by the game itself, players and platforms still try to mimic ways to obtain an approximate value of this metric as it can be used as a tool for comparing player's skill.

[1] http://euw.op.gg/

[2] http://www.lolking.net/

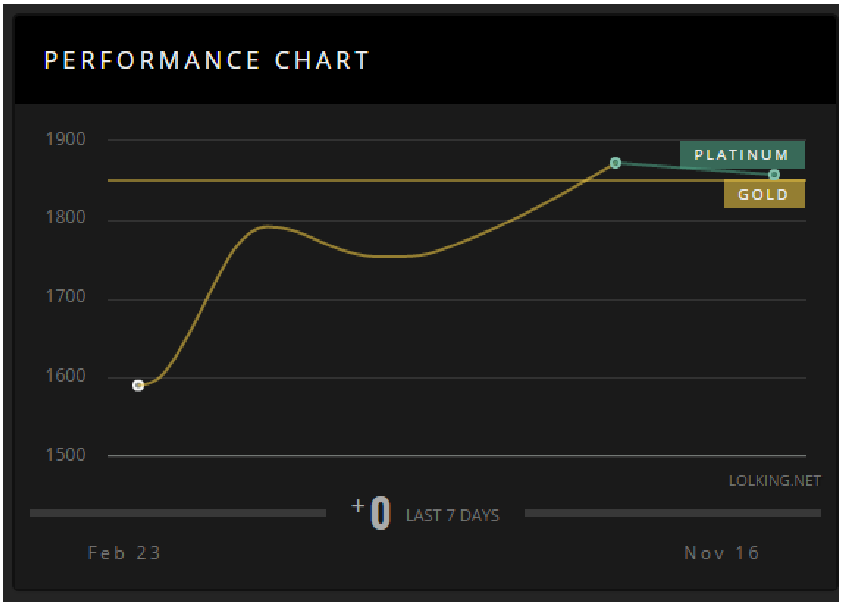

Figure 30 - LoLKing's player performance chart[1]

The analysis of champion performance across multiples matches is also performed to extract patterns and strategies employed. The results are presented using similar techniques as the ones mentioned so far (Figure 31). These views are frequently used by players who are trying to learn how to play new champions, since they can serve as a starting point to understand the mechanics surrounding it. Information regarding runes, masteries, builds and skill order are among the most frequently consulted.

Figure 31 - Champion performance analysis[2]

All the techniques used in these platforms rely mostly on statistical information, incorporating when possible the temporal aspect of the available data. The only instance where the use of the spatial component of data seems to be presented is in the official Match History application. Here, simple 2D static maps are displayed where the location of a player's death (Figure 32 (a)) and the location of all destroyed buildings (Figure 32 (b)) can be observed. However, these maps do not incorporate the temporal

[1] http://www.lolking.net/

[2] http://euw.op.gg/

component associated with this data, which means they only allow for a simplified analysis of the spatial information associated with the game events and the locations of the players.

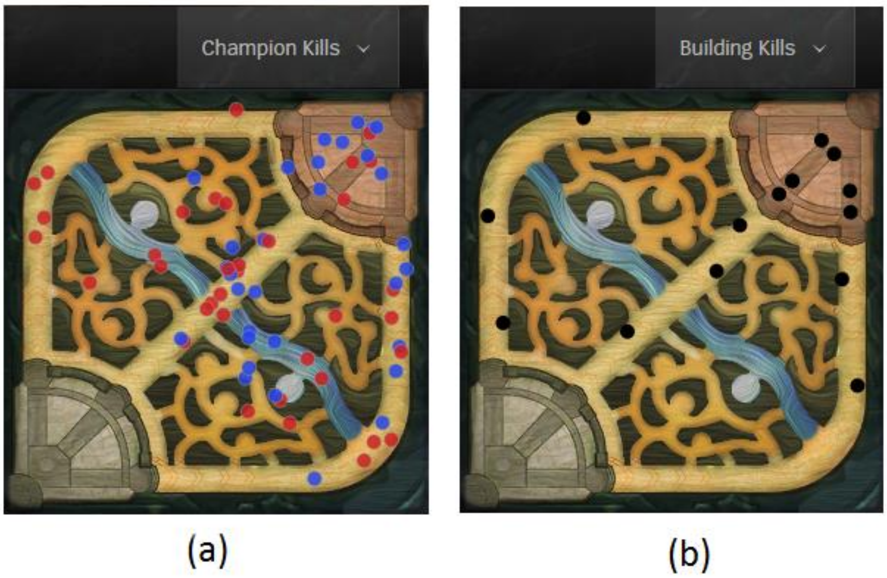

Figure 32 - Match History static maps[1]

The replay system developed by Riot Games (Figure 33) allows to play back and analyze the players' most recent matches. This system allows users to visualize any area of the map, the status (items, gold and combat stats) and location of players and all the events that take place during a match. This visualization has the option to ignore Fog of War and view the entire map without the restrictions imposed to players. There is also information about each team regarding the total number of structures destroyed, the number of dragons slain and the total amount of kills obtained.

The playback can be controlled via an interface similar to the one present in any video playback software. It allows users to pause and play the animation, as well as jump to any moment in the match with the use of a slider that doubles as a timeline to visualize the events that happened during the match. Although this approach gives users the ability to experience the full gameplay, it has its drawbacks. First and foremost, it requires the installation of the game to use the replay system, hence not allowing access from any device or platform. Secondly, due to the fact that this approach provides all the available information, and can require users to visualize the entire full length of the match, the analysis performed might be highly time-consuming. Lastly, in its current state, the replay system only allows players to visualize their twenty most recent matches, that were played since the last time the game was updated (every two to three weeks), which restricts analysis to a relatively small set of data. These restrictions can

[1] http://matchhistory.euw.leagueoflegends.com/

negatively impact users who are trying to improve their game expertise by observing other players. Nonetheless, as far as known applications go, this is the only one that provides a mechanism for users to visualize and interact with spatio-temporal data during analysis, namely player position and trajectory, and event location.

Figure 33 – Replay system

The analysis of these applications strongly suggests that the spatio-temporal components of the data are being neglected when analyzing player performance, as there are no techniques taking advantage of it. This, in conjunction with the conclusions resulting from the analysis of the state of the art, advocate for the exploration of visualization techniques that take advantage of the spatio-temporal components of the data to provide users with more and better information that can allow them to perform a richer and more complete analysis. The following section describes the developed prototype that aims to explore visualization techniques, in particular animated maps, to allow users to explore the spatio-temporal components of the data.

3.3 VisuaLeague Prototype

To provide a tool for player performance analysis, VisuaLeague focuses on the use of animated maps to represent the movement of the players during a match, as well as to display the events that took place. This analysis can focus, for example, in the trajectories players take or on their contribution to certain events that happened during the match. Other techniques, such as the ones used in other applications with the same purpose, were also employed to allow the visualization of thematic attributes like gold and items, although, only attributes that have a temporal component associated are represented. An overview of the developed prototype can be observed in Figure 34.

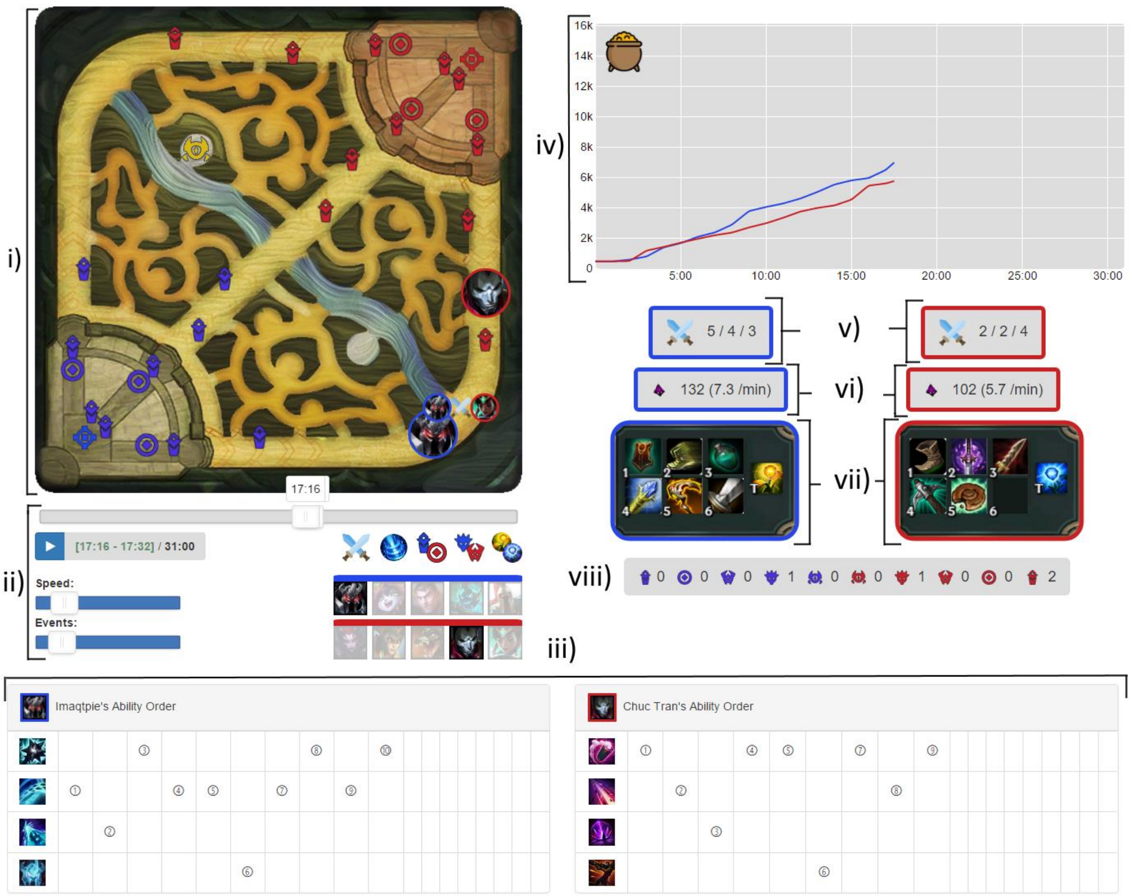

Figure 34 - Overview of the prototype

3.3.1 Technologies and Development Process

An iterative process was used to develop VisuaLeague, during which some players offered their input to guide the design decisions made. There was also a set of informal interviews that were conducted to validate existing functionalities, detect and correct possible bugs and guide the development. The application developed consists of a web application that can be interacted with using any web browser. The main technologies used to develop the prototype were PHP (for the back-end) and HTML5 (for the front-end). The PhpStorm IDE from JetBrains[1] was the main tool used to work with these languages. The Laravel PHP framework[2] was used as a basis to construct the back-end. This back-end provided functionalities that executed the various necessary calls to the Riot Games API to automatically fetch the data needed for the prototype to display information to the user. The Guzzle PHP library[3] was used to perform HTTP requests that contained the API calls. After executing these calls, the back-end transfers the JSON content of the HTTP responses, to the mechanisms in the front-end responsible

1 https://www.jetbrains.com/
2 https://laravel.com/
3 http://docs.guzzlephp.org/

by capturing and showing this information to the user. This process is conducted automatically, with the user only required to insert the name, region and the champion played (optionally) of the player he/she wishes to visualize in the front-end component.

The front-end was constructed using the Bootstrap framework[1] in conjunction with the jQuery JavaScript library[2], the d3.js JavaScript library[3] and the noUiSlider range slider library[4]. The Bootstrap framework was used as a simple and effective basis to construct the application layout, as it provides a grid system that makes it simple to position the various components on the application. The jQuery library was used as a means to communicate with the back-end portion of the application via AJAX calls. This library was also responsible by detecting and handling the various events that are triggered as a result of the user interaction with VisuaLeague. The d3.js library was used to construct the animated map (Figure 34 i)), the gold plot (Figure 34 iv)) and the item inventories (Figure 34 vii)). This library allows for the manipulation of SVG page elements with relative ease, which was essential to simulate the continuous movement on the animated map visualization. A similar approach was applied to the gold plot and the item inventory to simulate the variations over time of the metrics displayed in these visualizations. Lastly, the noUiSlider library was used to create all the sliders responsible for controlling the prototype. This library also provides mechanisms to capture the user interaction with the slider, which is later handled using jQuery.

3.3.2 Prototype Description

When opening VisuaLeague, the user is presented with a page (Figure 35) where he/she can perform a search for the twenty most recent matches played by a certain summoner. This page automatically searches for older matches as the user scrolls further down. As mentioned above, to perform the automatic search for match data, the user is required to provide the summoner name of the player, the region that player belongs to, and optionally a champion to filter out the results of the search. In this page, there is information regarding the outcome of each of the matches (green for victory and red for defeat), the champion and position played, when the match took place and its duration. By clicking on the details button on any of the search results, the user is presented with a page identical to the one shown in Figure 34, where the analysis of that match can be conducted.

[1] https://getbootstrap.com/
[2] https://jquery.com/
[3] https://d3js.org/
[4] https://refreshless.com/nouislider/

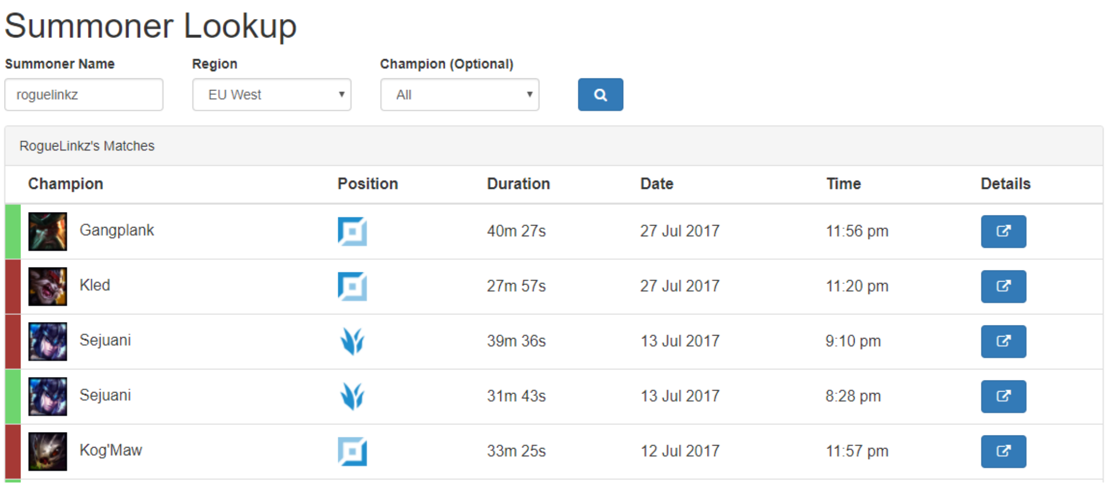

Figure 35 – Search page

As referred in Section 3.1.2, information regarding the position of each player is available roughly once every minute. This information allows the visualization of a simulation of the trajectories that players took during a match. Because the information about player position is only available once every minute, the trajectories simulated using only these points wouldn't be able to accurately describe the movements of a player during the match.

To create trajectories that were satisfactory and had a high degree of reliability, enough to allow this type of analysis, a graph was developed. The nodes of this graph represent places where a player can decide to change its path in a significant manner (Figure 36). The edges represent the path that a player can take from a node to another. It is important to mention that the edges of the graph do not go over walls or other obstacles present in the map. This way, the resulting paths represent routes that any player could have taken during the match because, even though it is possible to use certain in-game mechanics to transverse these barriers, not all champions can perform such actions and therefore they are not represented, as there is no information in the API about when and where these mechanics are used.

With this mechanism, if at time t_0 a player was in location P_0 with coordinates (x_0, y_0) and, at time t_1 the same player was in a location P_1 with coordinates (x_1, y_1) then, for both points, the Euclidian distance to the location each node of the graph is calculated to identify which are the nodes closest to these two points. Let's assume that these nodes are N_0 and N_1 respectively. After that, to create the approximate path the player took during the time between t_0 and t_1, the shortest possible path between N_0 and N_1 is calculated.

Figure 36 - Nodes of the graph

The path the player took during that time is then assumed to be the path calculated between these nodes. It is important to mention that this path is not necessarily a straight line between these nodes since, to go from node N_0 to N_1, it is very likely that one must pass by a set of intermediate nodes N_i that connect N_0 to N_1 in the graph. This algorithm is repeated for every pair of consecutive points that represent the position of each of the players. The total path the player took during the match is assumed to be the concatenation of all the calculated sub-paths. To more accurately create this final path, the position of several of the events where the player participated were also taken in consideration. Some of these events, such as the ones related to the item shop, do not have a spatial component associated but, since they can only be performed in one specific location on the map, that position was also added to the initial set of points that contains the location of the players. Furthermore, players can teleport back to the base at any given point. However, the occurrence of this event is not specifically provided in the information returned by the API. To simulate this event, it was taken into consideration that players need to be in their respective base to interact with the items shop, hence that would mean they either died prior to that event or teleported back before they bought the items. Taking this into consideration, to simulate the players returning to the base, the icons representing them in the map are instantly moved to their respective bases, prior to an event related to purchasing, selling or returning items. The representations of players were also instantly moved to the base after a small delay (respawn time) to represent what happens when a player dies.

The main component of the prototype is the animated map (Figure 34 i)), where players are represented in a similar way as the one present in the in-game map, using circles with the images of the chosen champions (Figure 37). These are the representations that will follow the paths calculated above to simulate player movement. The icons associated with players and structures are color coded, with blue representing the team in the southwest corner and red representing the team in the northeast corner. Global objectives are also represented using familiar symbols with a neutral color (yellow). With the current state of development of VisuaLeague, users can visualize the information of up to two players simultaneously, one from each team. The animated map allows users to visualize the evolution of the trajectories of the players over time, as well as the events where these players participated.

Figure 37 - Player, structure and global objective representation

The events are represented with the use of two or three icons in a row (depending on the type of event) in the location on the map where that event happened. Different symbols are used to represent different types of events. All of the symbols that were used are similar to the ones found inside the game environment, to facilitate the learning process when using the application. The represented events have three components: the individual responsible for the action, the action being taken and the target for that action.

Figure 38 - Event representation using three icons

Figure 38 shows an example of such an event where the red player killed the blue player. In this case the red player would be the individual responsible for the action, the action would be killing another player and the blue player would be the target of this action. Event representations with only two icons represent actions taken by a player that do not have a target, such as going back to base or placing a ward (Figure 39).

Figure 39 - Event representation using two icons

As mentioned above, most events have either a spatial component associated with them or can only occur in a specific place and thus, it is possible to represent them. That is not the case for ward events. In this case only the temporal component is available and, therefore, these events' location will be attributed to the place where the champion is when the event occurs. This decision might not reflect with total accuracy the location where interactions with wards took place but, it provides enough information that, in conjunction with game knowledge, might help users understand vision control strategies being employed.

The evolution of the trajectory and the events being shown on the map, as well as the information displayed in the other visualizations, evolve over time and can be regulated through a set of controls that can be observed in Figure 40. The slider in Figure 40 a) allows users to select the instant of the game they want to observe. This feature was essential to allow players to control what moment in time they are observing, much similarly to what they would be able to do when using the replay system.

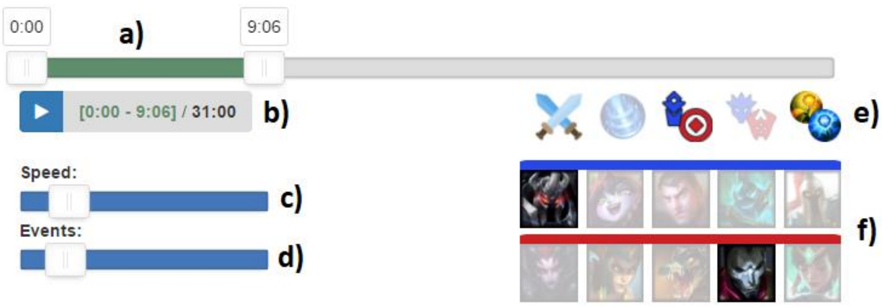

Figure 40 - Animation controls (zoom of Figure 34 ii))

When the animation is playing, this slider has one handler that controls the instant in time being observed in all the visualizations. When the animation is paused, two handlers are visible and the user can select an interval of time where all the events that happened during that period are shown in the map. In this mode, the position of the players in the map as well as the information in the other visualizations, corresponds to the time referenced by the handler that is farthest to the right. The solution using the two handlers was not initially conceived but, upon further discussion, it was concluded that it might benefit players who are interested in analyzing what events occurred during fixed periods of time, as well as to help users visualize the region of the map that was more impacted by certain players.

The mechanism in Figure 40 b) can be used to start, pause and restart the animation. Through it, it is also possible to view the current instant or interval being displayed, as well as the total duration of the match being analyzed. This feature, in conjunction with the slider mentioned above gives users full control of the animation being displayed in the map. The slider on Figure 40 c) further improves the control of the observed animation, by allowing users to adjust the animation speed, i.e., to adjust how fast time will advance, which directly reflects on the speed of the animation being displayed. The slider below it, Figure 40 d), allows users to control how long the representation of events is displayed on the map, after they took place, during the animation. This control was created so that users could adjust how the representations are displayed while the animation is being played, since the time needed to assimilate the information during playback might vary for each user.

The control on Figure 40 e) provides a mechanism to filter which types of events are displayed. It's important to mention that, apart from global events that are always represented, only events directly related to the selected players are displayed. This feature was designed as a means for users to filter out information related to some events that they might not find relevant to analyze a certain scenario. Lastly, the controls on Figure 40 f) allow users to select which players are being displayed. Even though, in the current state of the development, only a maximum of two players can be visualized at once, this feature was still introduced so that users can select and visualize data related to other players in order to extract information that can be useful in their analysis.

There's also six other components that complement the information displayed in the map with metrics commonly utilized in the analysis of player performance. The visualization in Figure 34 iv) allows users to observe the evolution of the total amount of gold accumulated over time by the selected players. This technique can be interacted with by hovering the mouse pointer over it to inspect the gold values referring to a certain moment in time (Figure 41). The KDA (Kills/Deaths/Assists) of the players is displayed in the visualization in Figure 34 v). This metric is important because it provides information related to kill participation, which is considered important to measure player performance. The fact that all the other platforms have a representation for this metric further demonstrates its importance.

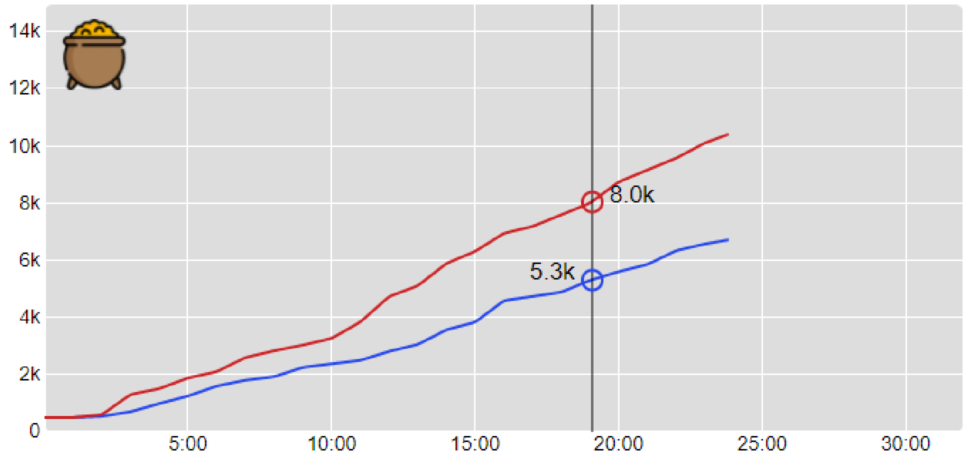

Figure 41 – Gold graph interaction

The number of minions slain is a metric that is directly related to the amount of gold a player can earn, hence its importance to analyze player performance. The visualization in Figure 34 vi) represents the total number of minions killed as well as the average number of minions killed per minute. Since the amount of gold earned by a player is directly correlated to the number of items he/she can buy, a representation of the item inventory was also added (Figure 34 vii)). Since this representation evolves over time, it allows users to study the decisions made in relation to items bought depending on the current situation of the player. A list with the global objectives that were conquered by each team can also be observed in the visualization in Figure 34 viii). This visualization includes the number of towers destroyed, the number of inhibitors destroyed, the number of Barons slain, the number of Dragons slain and the number of Rift Heralds slain for each team. This visualization helps users keep track of past events which facilitate the analysis. Lastly, there are tables that allow the visualization of which skills were learned at each level (Figure 34 iii)). Although this metric might not be as important as the others to analyze player performance, it provides information about the current capabilities of each champion, which in turn can help users justify some observed interactions.

The decision to include these visualizations, was also based on the study of the applications directed at player performance analysis performed in Section 3.2. Even though, the metrics displayed in the visualizations used in the applications may vary in terms of importance, depending, for example, in the role occupied by a player or the chosen champion, there seems to be a consensus that they contribute positively to evaluate the state of the game and the players. This can help users understand, among other things, the effect of the actions and events observed in the map and how far ahead a player is compared to others. Furthermore, since these visualizations incorporate the temporal component by changing as the animation unfolds, they provide a much richer analysis when compared to their static versions.

3.4 Summary

This chapter described the full process behind the development of VisuaLeague, as well as the resulting application. First, a detailed explanation of the video game League of Legends is made, where all the game mechanics and interactions are explained, followed by a description of all the telemetry data available for analysis of the matches from this game. Secondly, an analysis of the existing applications directed at visualizing player performance is presented, to study the techniques currently employed in the contexts surrounding this particular video game and to understand what metrics are currently presented to users.

Following that, a description of the development process used to create VisuaLeague is made, where all the tools and software used is explained. Lastly, the current state of development of VisuaLeague is described, by explaining in detail all the visualizations techniques that were applied and how they can be interacted with, as well as the relations between these techniques.

Chapter 4

Evaluation

Following the development of VisuaLeague, a user study was conducted aimed at understanding the importance of spatio-temporal information when analyzing player performance in the context of online video games. Furthermore, understanding if the visualization techniques applied met the needs of the users was also taken into consideration.

The evaluation of VisuaLeague was conducted in two phases. The first consisted of a set of informal interviews with several users that played the game frequently and used existing applications directed at evaluating player performance. The objective of this first phase was to validate the functionalities that existed at the time, correct possible flaws in design/implementation and get some preliminary feedback to improve and guide further research and development. During the second phase, a different set of individuals were invited to participate in a user study where participants were asked to perform several identification and analysis tasks using VisuaLeague. With the purpose of fulfilling the objectives mentioned above, users were asked to fill out forms when they were done performing the tasks, to identify used criteria, strategies of interaction and degree of satisfaction towards the approaches taken in the prototype.

This chapter presents the process conducted to evaluate the prototype. Section 4.1 presents the informal interviews that served as a guiding tool for development. Section 4.2 describes in detail the user study conducted to evaluate the current version of VisuaLeague, as well as the results obtained.

4.1 Informal Interviews

In the context of the event Dia Aberto[1] that took place in Faculdade de Ciências da Universidade de Lisboa, VisuaLeague was made available to several visitors that could freely interact with the application and test the available functionalities. In total, twelve

[1] https://ciencias.ulisboa.pt/node/4085

individuals, with ages ranging from 14 to 25, participated in these informal interviews. This group was composed of high school and college students that played League of Legends at least once a week. The opinions and suggestions expressed by participants were stored for further analysis.

During these interviews, participants showed interest in using VisuaLeague to evaluate their performance, as well as the performance of other players. They justified this by pointing out that taking advantage of the spatio-temporal components of data was an innovative approach when compared to existing applications that they currently used (namely, OP.GG and LoLKing), as it allowed them to visualize and analyze the variation of player position over time and the location of the events that occurred during the match. It was also possible to identify the type of information that participants focused on more frequently, namely, the destruction of buildings and events associated with the KDA of a player. However, some participants pointed as a negative aspect, the lack of statistical information and static thematic data (i.e., data that does not evolve during the game, such as runes and masteries) typically displayed in existing applications. Although it is a valid point, the objective of VisuaLeague is to allow users to perform spatio-temporal analysis and therefore, the inclusion of this type of information, at least at this point of the development process, did not seem necessary. Furthermore, is it not the objective of this work to create an application necessarily better than the existing ones but, to create one that explores visualization techniques that take advantage of the available data, and can contribute to improve them.

4.2 User Study

The second phase of the evaluation, consisted in a user study conducted with VisuaLeague, which aimed at: i) studying the importance of spatio-temporal information when analyzing the performance of players in the context of online video games; ii) understanding if users found the applied techniques, primarily animated maps, suitable to analyze spatio-temporal information in this context; iii) uncovering meaningful patterns of interaction and criteria considered important when analyzing spatio-temporal data; and iv) understanding how this implementation of animated maps can be further improved to meet the users' requirements.

The following sections will describe the study as well are the results obtained from it. Section 4.2.1 presents a description of the participants of this study. Section 4.2.2 describes the tasks that participants were asked to execute. Section 4.2.3 describes the methodology followed during the study. Section 4.2.4 describes the results obtained in the study. Lastly, Section 4.2.5 presents a discussion of these results.

4.2.1 Participants

Prior to performing the tasks, participants were asked to fill out a form with some profiling questions, e.g., sex, age and occupation. This form also included questions related to how long the participants had been playing League of Legends or similar games, what was their current ranking and which role they filled more frequently when playing LoL. Lastly, participants were also asked to disclose which applications they currently used for player performance analysis.

A total of thirty individuals participated in the study. Of these, twenty-nine were male and one was female, with ages varying between 17 and 31 (μ = 22,23; σ = 3,14). All participants were students, with 77% of individuals studying Informatics Engineering or related areas. The majority of participants were distributed across the three lowest ranking divisions of competitive play (Figure 42), with Gold being the division with the highest number of individuals.

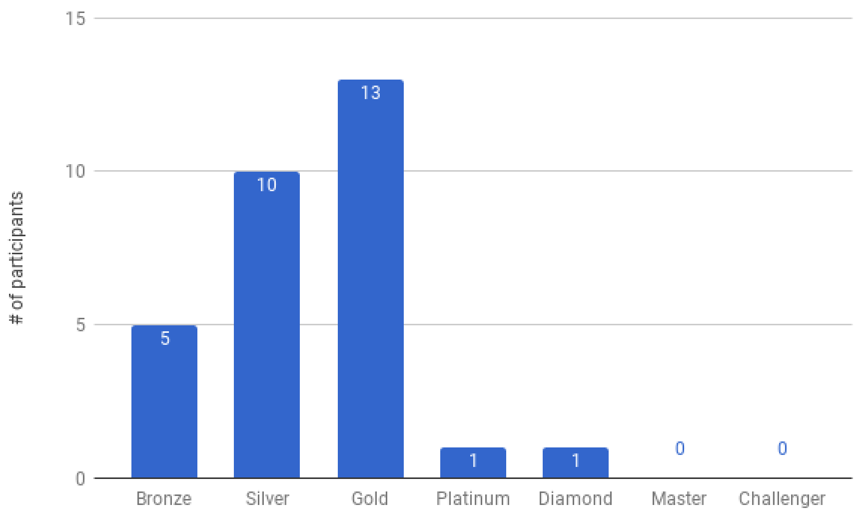

Figure 42 - Distribution of participant's ranking

Role distribution was more even, although, more than 50% of participants had a preference to play Bottom lane roles (ADC or Support) (Figure 43) that require a high degree of synergy to succeed. There were no participants without a preference in role played (Fill). In terms of experience with League of Legends or similar games, the majority of participants (80%) reported having been playing the game for at least three years (Figure 44).

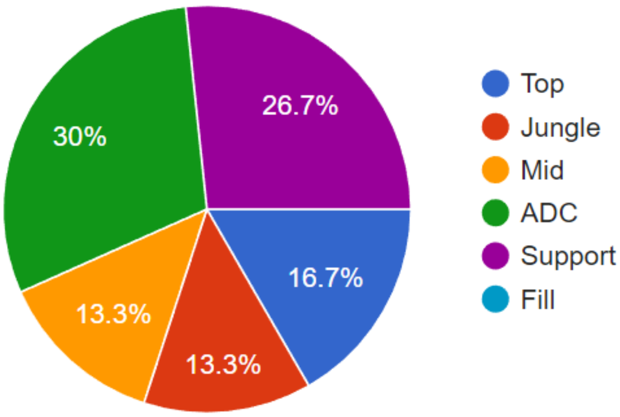

Figure 43 - Distribution of participant's preference of role

When inquired about what tools they used to review and analyze player performance after matches, 76.7% of participants mentioned using the official Match History web application regularly. Twenty-eight out of the thirty participants referred using a third-party application, such as OP.GG[1] and LoLKing[2]. It is important to note that only five participants mentioned using the replay system regularly, which is the only application that currently displays spatio-temporal data.

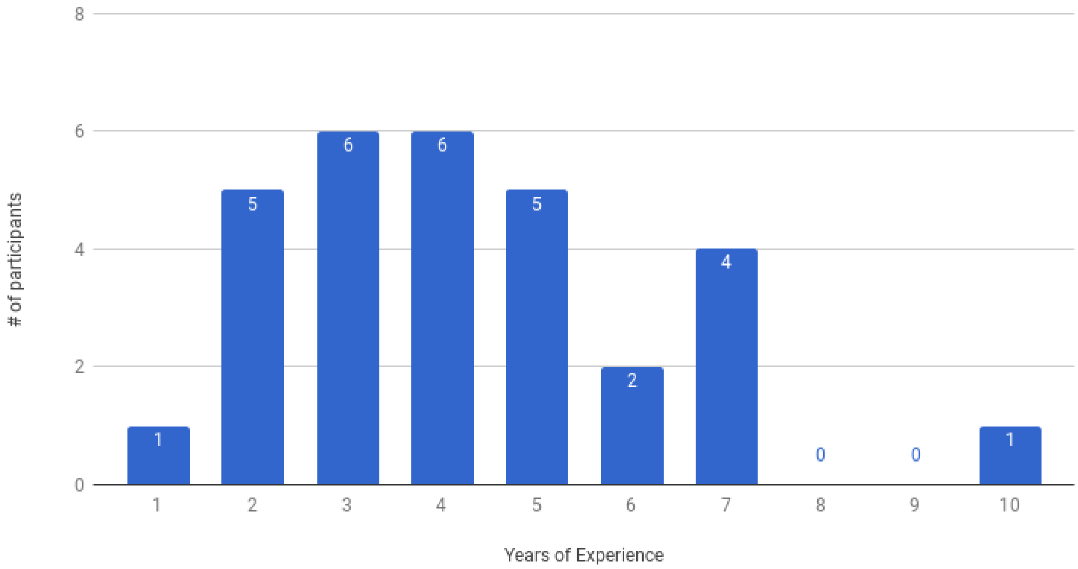

Figure 44 - Distribution of participant's experience (in years)

[1] https://euw.op.gg/
[2] http://www.lolking.net/

4.2.2 Tasks

Based on the observation of several professional matches, and the feedback from the informal interviews performed in the previous stage, five types of events were identified that are considered important to analyze player performance:

Player kill/death: whenever a player kills an opponent, it gives advantage to the enemy team in terms of gold and experience, but it also opens up the map for other plays since there are a numbers advantage from one of the teams who can use it to take other objectives. This type of event can happen anywhere in the map and at any given time.

Slaying Dragons: when the Dragon is killed, it provides the team who slayed it with gold, experience and enhancements in battle capabilities. This leads to players developing strategies around taking this objective to gain advantages over the enemy. This type of event can happen anytime during a match but is bound to a specific zone in the map.

Slaying Barons: similarly to Dragons, slaying the Baron also provides the team gold, experience and enhancements in battle capabilities. Although this event is also bound to a specific zone in the map (different from the one where the Dragon spawns), it can only occur after the 20th minute mark.

Destroying Towers: when a team destroys a tower, it gets rewards in the form of gold and experience. Players tend to develop strategies around grouping to facilitate the destruction of these objectives, hence its importance to analyze play performance. Events related to towers can happen at any time but, since towers are stationary structures, it can only occur in a fixed set of locations that does not change over time or from match to match.

Destroying Inhibitors: destroying inhibitors is essential to win the game. Players can only start attacking the enemy nexus when they have destroyed at least one inhibitor belonging to the enemy team. Unlike any of the other described events, when an inhibitor is destroyed, it does not provide gold or experience. Instead, it empowers the minions that occupy that lane which applies increasing pressure to the enemy team, typically requiring one or more players to permanently defend their base or they risk losing the game. Although this event can also happen anytime, it tends to happen in the later stages of the game. Just like towers, inhibitors are stationary structures located in much smaller geographical areas (the inside of team's bases), thus events related to their destruction can only happen in a fixed set of locations.

To evaluate player performance, it is important to understand the relation between the actions the players perform and their outcome. For this reason, in the context of this experiment, the participants were asked to execute two different tasks commonly performed by players, spectators and analysts, namely *associate*, and *comparison*.

In the *associate* task (T1), participants were presented with a scenario that features two players of opposing teams playing similar roles during one match. This task aims to simulate a common exercise performed by players, in which they analyze their actions and the actions of their peers, during a specific event, in an attempt to identify mistakes that can be corrected to improve their performance. This analysis is also very common in professional settings, for example, the individuals who live comment professional matches typically analyze the contribution of each player to an event to compare performances. The scenarios that participants were presented varied depending on the role that they most frequently played. This was done to help participants be familiarized, among other aspects, with the champions that players chose and the actions being displayed. During this task, participants were asked to first identify where and when certain events occurred, and who participated in those events. Following that, participants were asked to evaluate and classify, between 0 and 10, the performance of the players being analyzed, based on any set of criteria they considered relevant. The participants were also asked to justify that classification based on their selected criteria. This set of actions was repeated by the participants five times during this task, each referring to different events belonging to one of the types described above:

1. First of the two players to get killed (T1.1)
2. First Dragon slain (T1.2)
3. First Tower destroyed (T1.3)
4. First Baron slain (T1.4)
5. Last inhibitor destroyed (T1.5)

It is important to mention that, for the first event of the list, participants were only asked to identify when and where the event occurred and who participated in it, and it was not required to classify the performance of the players. This decision was made because during preliminary tests performed prior to this experiment, participants only justified the answers based on the change in KDA of the players.

In the *comparison* task (T2), the participants were asked to compare the performance of two players, from opposing teams, on a similar role, during different periods of the match, namely early-game, mid-game and late-game. Similarly to the *associate* task, the participants were free to select any criteria they considered appropriate and, at the end of the task, they were asked to indicate which of the two players had a superior performance, and to justify those decisions based on their selected criteria. The participants were also asked to classify the overall performance of the two players, between 0 and 10, and justify those scores. The purpose of this was to simulate an analysis commonly conducted in professional competitive environments, where players are evaluated and compared during these time periods to classify their overall performance during the game.

In both tasks, the criteria used by participants to justify their choices were intentionally left open with the purpose of understanding which metrics play an important role when trying to analyze player performance and how these criteria can differ from one participant to another. While participants were performing the tasks, VisuaLeague automatically recorded information regarding the interaction with the prototype (e.g., where the participant clicked) in a non-obtrusive manner, for further analysis.

After completing the tasks, the participants were requested to fill out a small questionnaire regarding their experience and satisfaction towards VisuaLeague. They were asked to classify, between 0 and 10, the importance of the information displayed on the animated map for their analysis. They were also asked if they thought they could reach the same conclusions if the animated map visualization was not present. To understand if visualizing more than two players simultaneously was beneficial, participants were asked if this feature would improve their analysis of player performance. These were followed by a series of seven usability questions, that required participants to attribute a grade between 0 and 10 to statements, depending on how much they agreed with them. During all of the questions, participants were encouraged to expand on their answers if they felt necessary. Lastly, there were three open-ended questions that requested participants to describe VisuaLeague's most positive and negative aspects, and to mention any final thoughts and suggestions that they might have. The tasks, as well as the questionnaire, can be consulted in Appendix A.

4.2.3 Methodology and Apparatus

The experiment took place in a room where subjects had access to a computer that could be interacted with using a mouse. The screen participants used had a resolution of 1680x1050px and was placed approximately 50cm away from them. VisuaLeague was previously loaded into a web browser with all the matches that could be used opened in different tabs. The matches were selected by the observer based on the preferences of the participant. During the first task, and at the end of each subtask, the state of the prototype was reset to its original configuration. During the experiment, the observer sat next to the participant, with access to a laptop to take notes based on the performed actions and the comments. It is important to mention that the participants were not able to inspect the notes taken by the observer during the experiment, as to not influence their answers or interaction methods.

The experiment was conducted following a *within-subjects* design and all participants carried out each task individually. At the beginning of the experiment, participants were briefed about the nature of the study as well as the functionalities of VisuaLeague. Then, participants were able to freely explore the prototype's functionalities, for as long as they desired, so that they could get familiarized with the controls and interface and were able to clarify any doubts. The data used during this training phase was originated from a match that is different from any of the matches used during the actual tasks. After this training phase, the participants were asked to perform both tasks, first the *associate* task and, then, the *comparison* task. To minimize possible learning effects, the order by which the events were asked during the first task followed a *Latin square* model (Table 5). For validation purposes, all the data used during the experiment derives from matches played by the author of this work, however, the participants were never informed about that fact. As previously mentioned, participants analyzed data referring to the roles they frequently fulfilled when playing.

Table 5 - Task order example

Participant #	Task Order
1	1, 2, 3, 4, 5
2	1, 2, 4, 3, 5
3	1, 3, 2, 4, 5
…	…
28	5, 1, 3, 4, 2
29	5, 1, 4, 2, 3
30	5, 1, 4, 3, 2

The following dependent variables were considered to measure the study's results:

Task completion time recorded from the moment the participant was instructed to being the task until he/she gave the final answer. This variable is used to measure task complexity and the efficiency of users.

Actions participants performed when interacting with VisuaLeague. This covers interactions with all the controls available below the animated map. This variable provides an additional measure of task complexity, as well as a starting point to understand interactions strategies employed by the users.

Number of actions performed can be used as a measure of task complexity.

Type of actions performed can be used to understand interaction strategies as well as the importance of certain components of the displayed data.

Accuracy of the participants when identifying the events. This variable serves as a method to detect possible design flaws that impair the ability of users to interpret the information displayed to them.

The grades attributed to players by participants of the experiment, as well as the justifications for those grades were transcribed. The scores attributed to players were noted to compare the degree of coherence of participants when evaluating the performance of players. All the justifications for the grades were transcribed to extract the criteria used to justify the scores. This information is going to be used to understand the role of spatio-temporal information when evaluating player performance. Furthermore, this information will be used to understand if specific roles are evaluated similarly by different participants.

At the end of the experiment, the participants were invited to answer to a small questionnaire covering their opinions regarding the VisuaLeague prototype, its features, and suggestions that they might have to improve the prototype.

4.2.4 Results

The following sections describe the main results obtained in the study. For a matter of simplification, these focus on the most significant results obtained, those close to be considered as such, or that may reveal important patterns. The first section is focused on analyzing the quantitative data recorded during the experiment. The second section describes the qualitative analysis performed on the answers given by the participants.

4.2.4.1 Quantitative Analysis

This section is focused on analyzing the quantitative data, such as the information automatically recorded by the prototype, as well as the grades assigned to the players by participants. An analysis of the answers of the questionnaire will also be made.

Task Completion Time

To compare the differences in terms of task completion time in the different tasks, the results were subjected to the Shapiro-Wilk test of normality. Since no valid data transformation could provide a normalized dataset, a non-parametric approach was used by applying the Friedman method, followed by a Wilcoxon signed-rank test (SRT) with a Bonferroni correction, for pairwise comparisons of the different subtasks in the first task. The second task was not compared with the first due to its continuous and extended nature that would result in a more prolonged time needed for completion.

Figure 45 shows the participants' distribution of task completion time for each of the tasks/subtasks. A clear increase on the average time needed to complete each of the subtasks of the first task can be observed as the task number increases. In the *associate* task, the tests revealed a statistically significant difference in task completion time depending on which subtask was being performed ($\chi^2(4) = 34{,}074$; $p < 0.0001$).

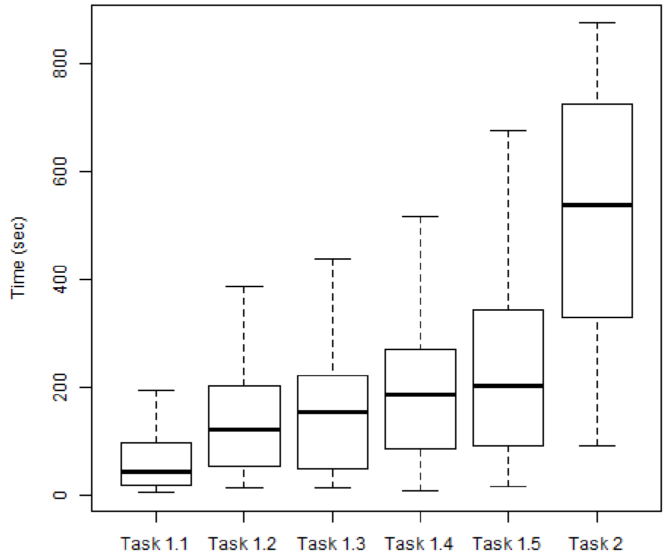

Figure 45 - Distribution of completion time

Post hoc analysis with the Wilcoxon signed-rank test, revealed significant differences between the first subtask and the others. A significant difference was also revealed between subtask two and subtasks four and five. The results can be observed in Table 6. Cells with a green background indicate significant differences ($p < 0{,}005$).

Table 6 - Wilcoxon SRT results for the task completion time

	T 1.2	T 1.3	T 1.4	T 1.5
T 1.1	V = 74 p < 0.005	V = 59 p < 0.005	V = 35 p < 0.005	V = 9 p < 0.005
T 1.2		V = 194 p = 0.44	V = 81 p < 0.005	V = 74 p < 0.005
T 1.3			V = 185 p = 0.339	V = 94 p = 0.021
T 1.4				V = 147 p = 0.324

Actions

The information collected automatically by the application during the experiment was analyzed in relation to three different aspects, namely the total number of actions performed, the relative play time of the animation and the speed of the animation.

To compare the number of actions performed by participants throughout the experiment, the same method applied in the previous section was used. In line with the decisions made for the previous metric, the second task was also not compared. The participants' distribution regarding the number of actions necessary to execute each of the tasks/subtasks is shown in Figure 46. A slight increase on the average number of actions can be observed in each of the five subtasks. The tests revealed significant results in the *associate* task ($\chi^2(4) = 28{,}157$; $p < 0.0001$). The pairwise comparison revealed a significant difference between the first sub-task and all the other sub-tasks in terms of actions needed to answer (Table 7).

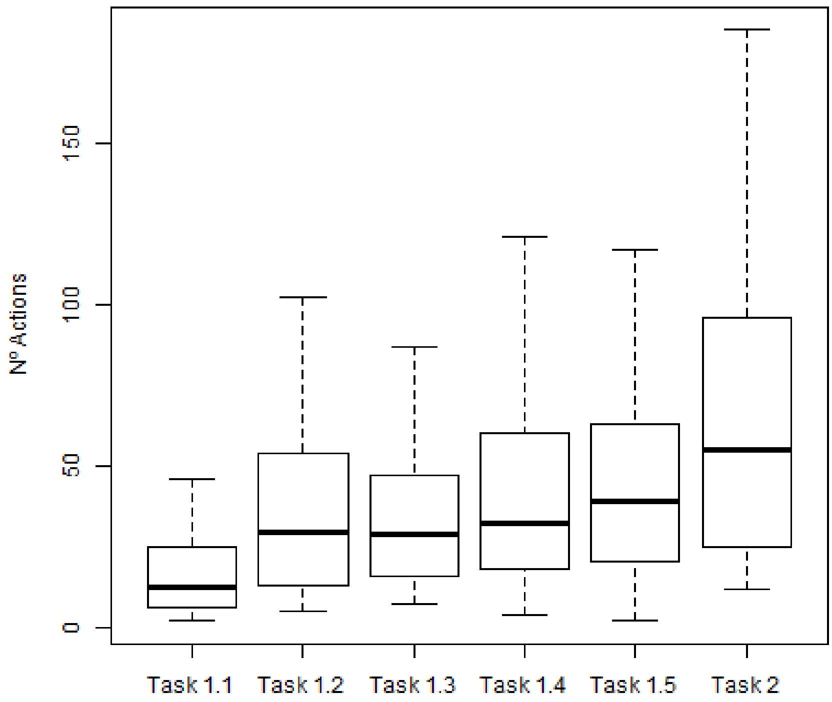

Figure 46 - Distribution of number of actions

Table 7 - Wilcoxon SRT results for the number of actions

	T 1.2	T 1.3	T 1.4	T 1.5
T 1.1	V = 84.5 p < 0.005	V = 94 p < 0.005	V = 60 p < 0.005	V = 14 p < 0.005
T 1.2		V = 208.5 p = 0.909	V = 125.5 p = 0.028	V = 141.5 p = 0.258
T 1.3			V = 177 p = 0.387	V = 107.5 p = 0.051
T 1.4				V = 182 p = 0.875

The animation speeds were compared by applying the same tests used in the data relative to the number of actions. Here both tasks were compared to understand if there was a significant change on the speed used when evaluating a continuous set of events, when compared to the analysis of isolated events. The test revealed significant results ($\chi^2(5) = 15$; $p = 0.01036$). Pairwise comparisons tests revealed a significant statistical difference between the speeds used in the second task and the subtasks one, two and three (Table 8). The distribution of the animation speed can be observed in Figure 47. The horizontal line denotates the default animation speed used by VisuaLeague.

Table 8 - Wilcoxon SRT results for animation speed

	T 1.2	T 1.3	T 1.4	T 1.5	T 2
T 1.1	V = 142 p = 0.626	V = 100 p = 0.095	V = 185 p = 0.933	V = 124 p = 0.948	V = 320 p < 0.005
T 1.2		V = 77 p = 0.038	V = 138 p = 0.743	V = 113 p = 0.673	V = 253 p < 0.005
T 1.3			V = 231 p = 0.531	V = 155 p = 0.898	V = 331 p < 0.005
T 1.4				V = 122 p = 0.637	V = 263 p = 0.027
T 1.5					V = 216 p = 0.018

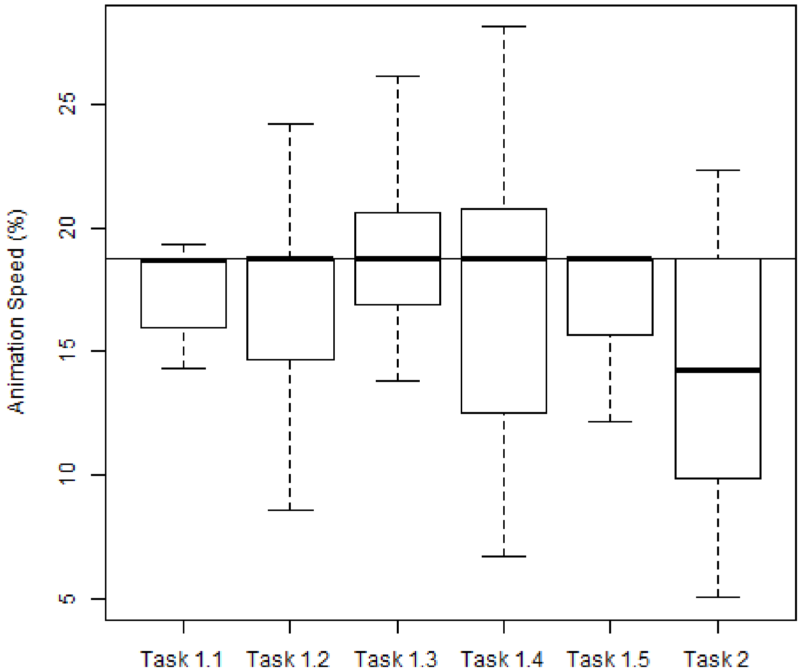

Figure 47 - Distribution of animation speed

The relative play denotes the ratio of time spent with the animation playing during the interaction with the prototype. This variable was also subjected to the Friedman test but no significant results were detected ($\chi^2(5) = 6,6023$; $p = 0,2519$). The distribution of these values can be observed in Figure 48. Although the tests revealed no significant results, by observation of the distribution of this metric, it's possible to see that on average participants had a relative play time of 40% or less, meaning that they spent less than half of the time expended to complete the task watching the animation, without interacting further with the prototype.

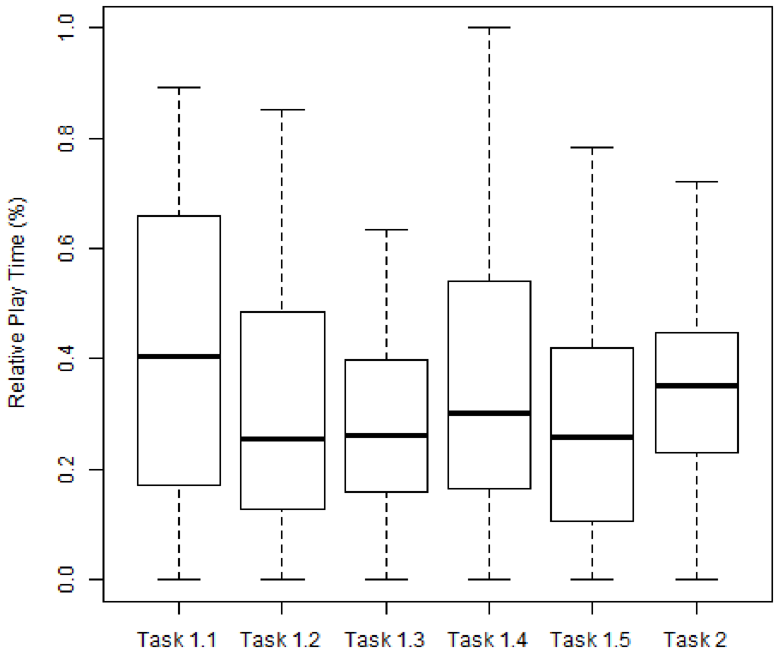

Figure 48 - Distribution of relative play time

Accuracy

During the experiment, there were only three instances where participants failed to identify the correct event. All these occurrences were made during different subtasks of the first task and by different participants. In these instances, participants concluded that they made a mistake (without the interviewer explicitly informing them) when they were justifying the answers. Since the total amount of errors committed by participants was so low, there is no point in performing a statistical analysis of this variable.

Grades Assigned

To analyze the agreement ratio between the grades attributed to the players by the participants of the study, it was necessary to divide the classifications for each role and each of the tasks/subtasks. The comparison made only evaluated the relative value of the grades made by participants, meaning that the results where only compared to understand if participants graded the same player has having a better performance. Since the instances mentioned in the previous section referred to events that were erroneously identified, that information was not considered for this analysis. The results can be observed in Table 9.

Table 9 - Concordance ratios of classifications

Role	Task 1.2	Task 1.3	Task 1.4	Task 1.5	Task 2	Role Average
ADC	100%	100%	89%	89%	89%	93%
Support	63%	100%	50%	88%	38%	68%
Mid	75%	100%	75%	75%	100%	85%
Top	60%	60%	80%	100%	100%	80%
Jungle	100%	75%	100%	50%	100%	85%
Task Average	80%	87%	79%	80%	85%	82.17%

On average, participants agreed 82,17% of the time on which player had a better performance, going as high as 93% for subjects who analyzed the ADC role. The lowest agreement rate (68%) was among participants analyzing the Support role.

Questionnaire Answers

To analyze the results of the questionnaire, the average values of the grades attributed to each of the questions related to user satisfaction were calculated (Figure 49). The results show that the participants had a positive opinion towards VisuaLeague, referring that the prototype was very easy to use and did not require too much effort on their part to interact with. They also graded the prototype as useful, mentioning that they had a high level of satisfaction towards it. The only aspect that was graded lower, was that the prototype did not save time when compared to the applications that the participants frequently used for player performance analysis. The participants indicated that this was not necessarily a negative aspect, adding that this approach fills a niche between the replay system present in the game, because it allows them to perform a deep analysis of the entire match using spatio-temporal data, and the applications they utilize online do not incorporate the spatio-temporal components of data.

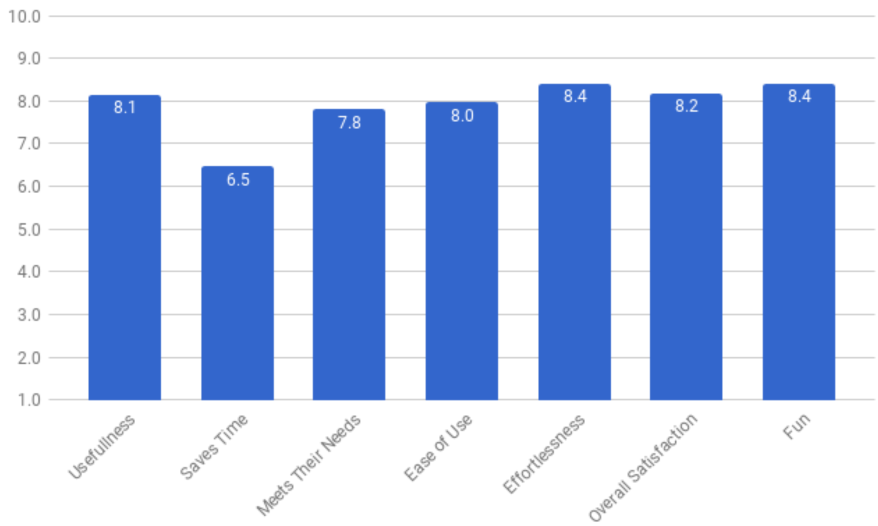

Figure 49 - Averages of the grade attributed on the final questionnaire

Most participants also pointed out that they would prefer the option to visualize spatio-temporal data to aid their analysis. Furthermore, when participants were asked how important the spatio-temporal information present on the map was to their analysis, on average, they attribute a score of 9.1 on a scale from 1 to 10. Twenty nine out of the thirty participants improved further on this topic by answering negatively when asked if they thought they could have reached the same conclusions and create elaborate justifications without having access to the spatio-temporal component of the data available through the map. One of the participants even pointed out that "*(...) with the other visualizations I can know how far ahead a player is compared to the others, but that does not necessarily translate in a big impact or performance in a certain event. That player might be dead. His death might have been the reason why his team is losing an objective because he played carelessly with his lead. Without knowing where he is and what he is doing it is hard to analyze these points of view.*".

4.2.4.2 Qualitative Analysis

This section is focused on analyzing the qualitative data transcribed during the experiment, such as the answers given by participants to justify the grades they attributed to players. The objectives of this analysis are to understand the role of the different components of data when analyzing player performance, and how individuals use these components to justify their answers.

The first step in analyzing these results was to create a set of codes to categorize the answers given by the participants. An iterative coding process was followed where two researchers (Pedro Vieira and Tiago Gonçalves) conjointly created a codebook. Each researcher coded the answers given by the participants separately, during which the codebook was refined and merged. A Cohen's κ measurement was performed to determine the agreement of the two resulting codifications attributed to the answers. The results showed that a significant degree of agreement between the researchers' codifications was achieved ($\kappa = 0{,}79$). A comprehensive list of these codes can be found in Appendix B. The codes with a green background refer to notions that are directly related to the spatio-temporal components of the data. This set of codes composed 39% of the total code usage. As can be seen in Figure 50, the top two most frequently used codes, LF (location far) and HP (help provided) are both part of this group. Furthermore, OP (objective participation) and EK (enemy kill) are strongly related to spatio-temporal notions, since they imply that a user must be in a certain location to participate in an objective or a kill event. The AP code (advantage player), despite not being directly related to the spatio-temporal components of the data, is a relevant metric to analyze player performance, as it describes the ability of a player to create an advantage over his opponent.

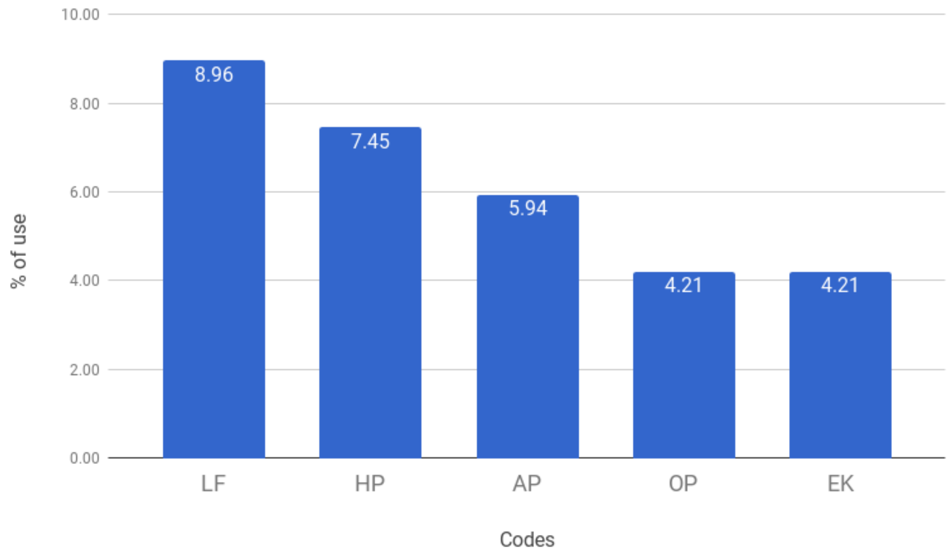

Figure 50 - Top five most frequently used codes in justifications

Criteria

An analysis of the codes attributed to the answers was performed to understand if there were any variations on the used criteria depending on the role being analyzed. This analysis consisted on looking at the codes attributed to extract the top three most frequently used criteria (MFUC) of each participant and of each group of participants that analyzed the matches of the same role. The results show a more frequent use of some metrics depending on the role being played. For participants evaluating the Top lane role (Table 10), the justifications tend to be more often based on the location of the player (LF), having an advantage over their lane opponent (AP) and helping other teammates (HP).

Table 10 - Top role criteria

Participant	MFUC	2nd MFUC	3rd MFUC
P8	HP	LF	AP
P9	LF	AP	HP
P13	OP	AP	CT
P15	LF	AP	HP
P26	LF	HP	AP
Group	LF	AP	HP

The Jungle role (Table 11) was judged most frequently based on their ability to perform ganks (AG), and whether or not these actions were successful (Asuc/Afail). Participants also pointed out player position (LF) as an important factor to analyze performance.

Table 11 - Jungle role criteria

Participant	MFUC	2nd MFUC	3rd MFUC
P4	AG	Asuc	Afail
P17	LF	AG	HL
P25	AG	OPF	Vis
P27	AG	LF	Asuc
Group	AG	LF	Afail/Asuc

The participants evaluating the Mid lane role (Table 12), justified their answers frequently using the same criteria as the Top lane role, pointing out that helping teammates (HP), player location (LF) and advantage over their direct lane opponent (AP) were important factors in judging player performance.

Table 12 - Mid role criteria

Participant	MFUC	2nd MFUC	3rd MFUC
P6	AP	Acons	LF
P10	LF	HP	AP
P22	HP	LF	Alimp
P28	HP	AP	Afail
Group	HP	LF	AP

The largest group analyzed, the participants evaluating the ADC role (Table 13), focused on criteria like player location (LF), number of kills accumulated (EK) and participation (or lack of participation) in objectives (OP).

Table 13 - ADC role criteria

Participant	MFUC	2nd MFUC	3rd MFUC
P1	EK	Alimp	OP
P3	LF	OP	DAP
P19	LF	AP	OP
P5	LF	Acons	OPF
P23	SD	Acons	OPF
P2	OP	OPT	OPF
P12	Hyp	KDA	EK
P18	OPF	OP	OPT
P29	EK	OPF	LF
Group	LF	EK	OP/OPF

Lastly, the group of participants analyzing the Support role (Table 14) focused on criteria related to helping teammates (HP) and player location (LF). They also mentioned that vision control (Vis/VL) was an important measure of player performance for this role, as well as accumulating assists (Ass).

Table 14 - Support role criteria

Participant	MFUC	2nd MFUC	3rd MFUC
P7	HP	LF	OP
P11	LF	Ass	VL
P14	Vis	VL	Alimp
P16	LF	VL	AP
P20	Ass	HP	OP
P21	HP	LF	Ass
P24	Alimp	OPF	OPT
P30	Ass	LF	VL
Group	HP	LF	Ass/Vis/VL

Analysis Profile

Based on the participant's answers, it was possible to discern different types of approaches that individuals adopted when justifying their answers with the information they were observing. Three major groups, which will be addressed as analysis profiles, were identified, namely, *Narrators*, *Storytellers* and *Speculators*.

The *Narrators* are the users who justify the answers only based on the description of the events/actions being observed. They also mention differences in gold, items and KDA.

"*This player had a better KDA but did not participate in a lot of global objectives since he was never near them when they were being contested.*" – Participant 1

The *Storytellers* go a step further and use all the information the *Narrators* use but discuss the relations between the actions and the events being observed. They often use their own game knowledge and experience to justify certain aspects of the observed gameplay.

"*This player was ahead in terms of KDA and gold. Because of that, and the fact that the champion being played is a good split-pusher, she played more by herself and tried to pull attention to her which was the reason why she didn't participate as much in objectives.*" – Participant 29

The *Speculators* had a behavior similar to the *Storytellers*, but went a step further by elaborating complex non-verifiable narratives based on what was being observed. Although these narratives did not always fully align with the events that took place during the game, they were plausible scenarios that could be considered valid to justify the performance of players.

"*(...) During this phase of the game there was a fight in mid lane that allowed his enemy to push and take down the inhibitor. However, since the red team overextended, they got chased down the lane and some members ended up dying. On the other hand,* *his team over chased as well which lead to some of his team members dying, which allowed for the red team to end up with Baron buff. (...)*" – Participant 5

The justification given by Participant 1 focused solely on indicating that the player had an advantage on certain metrics like KDA and that he was not near the location of objectives, which fits the profile of a *Narrator*. On the other hand, Participant 29 mentioned the metrics that he deemed important, which were coincidentally the same ones used by Participant 1, but he created a story based on his game knowledge that justified the actions of the player. He also mentioned the fact that the advantage the player had in terms of KDA and gold could be used for his team advantage by adopting a certain playstyle (*Storyteller*). Lastly, as part of his justification, Participant 5 described a set of sequential events that he was able to relate to each other by speculating the decisions made by a team and the consequences they had (*Speculator*).

Further analysis on these profiles was performed by analyzing the relation between player experience and rank with the profile they were attributed based on the justifications they gave. A Spearman's Rank-Order Correlation was run to determine the relationship between the participants' game experience, rank and profile. The results (Figure 51) show that there is a strong positive correlation between the game experience and profile attributed (r_s = 0,594, p = 0,001). No significant relationship was found between participant's rank and the profile attributed (r_s = 0,234, p = 0,213). The distribution of the experience of each group can be observed in Figure 52.

Correlations

			Profile	Rank	Game Exp.
Spearman's rho	Profile	Correlation Coefficient	1,000	,234	,594**
		Sig. (2-tailed)	.	,213	,001
		N	30	30	30
	Rank	Correlation Coefficient	,234	1,000	-,017
		Sig. (2-tailed)	,213	.	,929
		N	30	30	30
	Game Exp.	Correlation Coefficient	,594**	-,017	1,000
		Sig. (2-tailed)	,001	,929	.
		N	30	30	30

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 51 - Results of the Spearman's Rank-Order Correlation

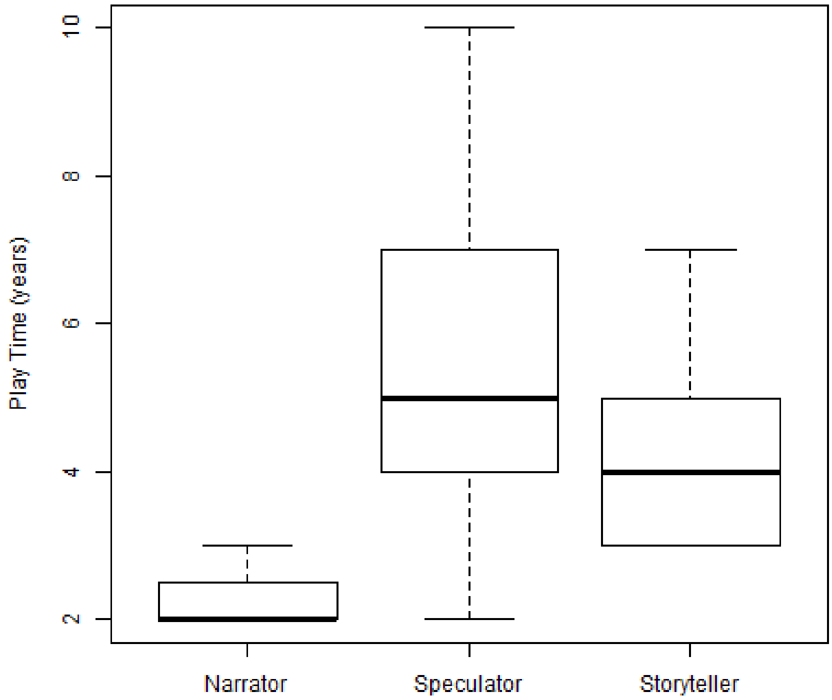

Figure 52 - Distribution of experience for each group

Interaction Strategies

During the experiments, the participants were observed as having three main interaction strategies with the animated map. Some participants simply watched the animation unfold and stopped when they were either ready to answer or needed to replay a certain chunk of time. This behavior can be considered as being a more passive approach towards the technique presented. On the other side, some participants very rarely played the animation. Instead, they would use the handlers on the slider to seek out and precisely observe a certain moment in time. They would also simulate the animation themselves by dragging the sliders very slowly to view the events, as well as the trajectory of players unfold. This behavior can be considered as a more active interaction approach. Lastly, there was a group of participants that played the animation up until they decided an event required a more careful analysis. When this happened, they would adopt a behavior similar to the one adopted by the second group mentioned, and would slowly drag the handlers themselves to carefully inspect the information present on the map.

In terms of usage of the event filters, there were no significant behaviors that could be observed, since all the participants used these filters to prevent them from observing events they did not deem relevant enough to answer a specific question. The player selection panel was used by nineteen out of the thirty participants which had two main interaction strategies. Some of these participants used this feature, when the animation was paused, to check the current position of other players in relation to the player being evaluated. These individuals however, did not analyze the trajectories of the other players, but focused instead on the relative position between the players in a single moment. This behavior was more frequently observed in the analysis of team fights that occurred during the same timeframe as the event being analyzed. The other participants adopted a strategy where they would analyze the other players' position and trajectories prior, during and after an event to understand if their contribution impacted somehow the performance of the player being analyzed. Here, participants used the animation to play the same interval of time repeatedly, with different players selected, to understand their contributions during that period.

Although the participants' interaction with the slider differed from person to person, most participants mentioned that they would like to see some changes to the current implementation of this feature. Some participants suggested that the slider should be changed to always feature only one handler, and to behave similarly to the sliders used to control video playback (S1). Some participants suggested a revision of the functionality of the slider responsible for controlling how long events are displayed on the map to complement this change on the main slider. Instead of its current function, this secondary slider would control how far back events would be shown from the current moment being displayed. Within these users, there were some that mentioned that they did not mind that the current design of the slider was maintained (two handlers) but that it had to be the non-default behavior even when the animation is paused. A second set of participants suggested that the current implementation with two handlers was adequate but it needed further improvement (S2).

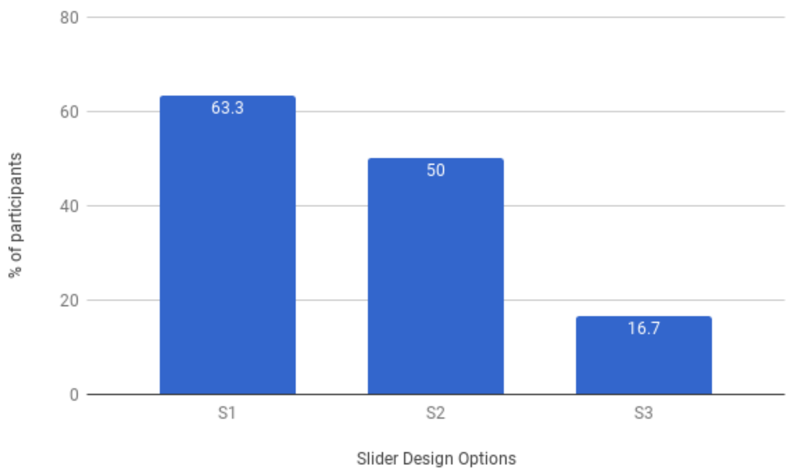

Figure 53 - Percentage of participants who suggested each design option

They pointed out that on occasion, the two handlers would overlap and it would be hard to distinguish which was the handler that controlled each of the boundaries of the interval being displayed. It was also mentioned, that it was frustrating when the handlers overlapped, and the users attempted to move the visible handler, nothing would happen because they were pulling the handler responsible by the opposite boundary they were trying to adjust. Lastly, five of the participants mentioned, that despite their recommendations to change the current state of the slider, they would like a new feature that would allow them to select a time interval to loop the animation (S3). The resulting percentage of players who mentioned each of these changes to the slider can be seen in Figure 53.

Questionnaire Answers

During the final questionnaire, users were asked to leave any comments and suggestions regarding VisuaLeague. They were also asked to mention the prototype's most positive and negative aspects.

According to the participants' opinions, the most positive aspect of the prototype was the possibility to observe spatio-temporal data. They mentioned that this approach was innovative when compared to the traditional applications. The animated map, despite having room for improvement, provided information that complemented the other components and aspects of the game that are typically analyzed, such as runes, masteries and item builds. Participants also pointed out that it was interesting to be able to observe the other visualizations in sync with the information on the map as it provided "*a stronger understanding of the decisions made by the player under analysis*".

The most negative aspects mentioned had to do with the problems encountered with the slider mentioned in the previous section. Some users also pointed out that, although it was not directly a problem with the prototype's features, the lack of more frequent data about the positions of the players, affected the usefulness of this technique. Some also mentioned that the existence of accurate information about the positioning of ward events would dramatically improve their analysis. Lastly, some users also mentioned the overlapping of events on the map as an aspect that hindered their analysis.

On the subject of suggestions, a significant number of participants (63.3%) mentioned that, it would be beneficial for their analysis, to visualize multiple players (more than two) simultaneously, keeping in mind that one of the problems with the map itself, the overlapping of events, had to be addressed first for this feature to work properly. This solution could also be extended to the other visualizations by finding a technique that allows all the players to be represented simultaneously. Participants suggested that, to solve the overlapping problem, all events could be represented with simple numbered marks that would be mapped to a feed on the side of the map, that would show events chronologically with all the information available about them. Another suggestion was to maintain the current implementation but, when the number of events in a certain area reached an elevated amount, they would be grouped as a new symbol that when hovered would show in detail what happened in chronological order in that area. A comprehensive list of all the suggestions made can be observed in Table 15, as well as the percentage of players who suggested each of the changes in Figure 54.

Table 15 – Suggestions

Sugestion Code	Description
C1	Visualize multiple players (more than two simultaneously)
C2	Global score
C3	Statistical/static information
C4	Aesthetic aspects (background color, order of visualizations, select visible visualizations, etc.)
C5	More features on the gold graph (team total gold, current gold, etc.)
C6	Fog of war
C7	Visualization similar to ingame to view player avatars and their status (alive/dead)
C8	Timeline of events (similar to match history)
C9	Information that results from multiple game analysis
C10	Different visualization of events (explicitly see assists, more information on hoover, etc.)
C11	Resolve overlapping of events in the map

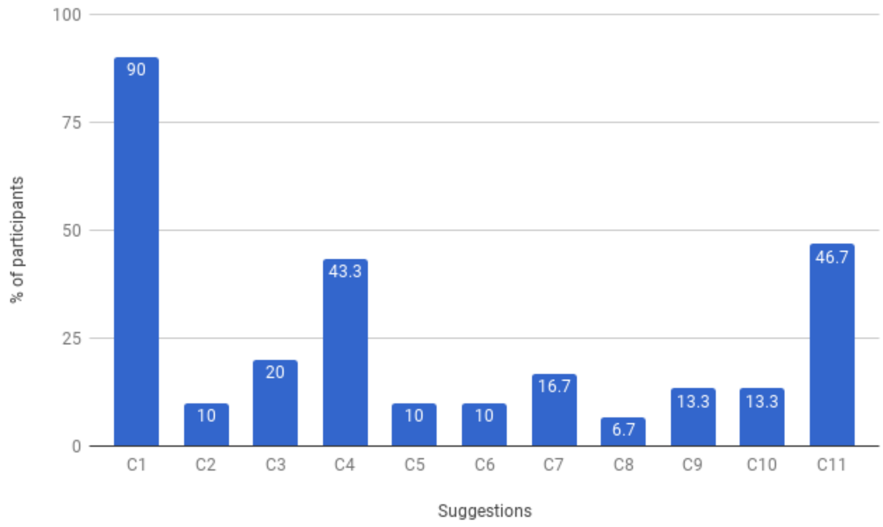

Figure 54 - Percentage of participants who suggested each of the changes

4.2.5 Discussion

The quantitative results obtained, alongside the participant's subjective feedback highlight some relevant aspects regarding the VisuaLeague prototype, its components, and the way participants interacted with it.

In terms of task completion times, the results show a significant difference between subtask one and all the other subtasks. This difference can be attributed to the lack of need for grading of the players and justification by the participants, hence it is not relevant to understand if there is an actual difference in how users interact with VisuaLeague depending on the task at hand. However, subtask 2 also showed a significant difference between subtasks 4 and 5. The event players are asked to identify in this task (the killing of the first Dragon of the match) typically occurs in the earlier stages of the match (prior to 10 minutes) and not many players tend to participate in it. The first time this objective is seized is also commonly uncontested due to lack of vision or unawareness by the other team. These factors lead to the complexity in detecting and analyzing this event to be lower than the events that happen in the later stages of the game, such as slaying the Baron (subtask 4) and destroying Inhibitors (subtask 5). During these stages of the game, players tend to adopt a playstyle that requires them to group more often, making it easier to control vision and to contest objectives, which leads to the events surrounding these objectives involving more players and, consequently, having a higher degree of complexity. These patterns, alongside the results obtained regarding task completion times, suggest that users take longer to analyze the contribution to these objectives because of the number of events surrounding the objectives being higher and more complex. To back this claim, on average, the number of actions users executed when performing subtasks 4 and 5 was also slightly higher than on tasks 2 and 3.

The analysis of the animation speed also yielded similar results. Not only the average speed was lower on tasks deemed more complex to analyze (subtasks 4 and 5 and task 2), but the tests reveal a significant difference between the animation speed used in subtasks 1, 2 and 3 and task 2. Since task 2 required careful inspection of the entire match, the degree of complexity of the analysis was higher than when analyzing isolated events, therefore users required slower animation speeds to be able to understand the relationships between the observed events. The results of this analysis also point out to users preferring overall slower speeds when compared to the one offered by default. This result can have implications on the design of the animated map, since it implies that users want precise control over the animation speed. The number of actions performed during the tasks is a good indicator that despite the fact that the prototype revolves around the use of a technique that arguably promotes a passive analysis, the participants leaned towards a more active approach that frequently required interaction.

During the experiment, the rate of success when identifying events was extremely high. This leads to the conclusion that the current visualization is appropriate to display the events taking placing during a match. However, as participants pointed out, it is necessary to solve issues of overlapping of information when there’s a high number events happening in a small area, as it hinders their ability to analyze the match.

The analysis of the results of the grades assigned reveal that users tend to agree on which player(s) performed better during a match based on the information displayed. One of the lowest agreement rates observed was among participants analyzing the Support role. This situation is expected, as this role is open to multiple viable strategies that might not be considered by everyone as optimal, which leads to disagreements based on the used criteria. The analysis of the used criteria suggests that not only the relative grade assigned has a high agreement rate, but the criteria used to justify these grades is frequently the same. By looking at the results of the frequency in criteria used during the analysis of each role some valid points stand out. The two lanes that are usually played by only one player (Top and Mid) have a tendency to be evaluated based on the capability of the player to take a solo advantage over his lane opponent. Not only that but, players are evaluated on how well they can help other teammates with that lead and how well they can use it to pressure and participate in objectives. On the other hand, players on the Jungle role were mostly evaluated based on their ability to impact other lanes with ganks, and most of all, if those actions are successful or not. Lastly, the two roles played in bottom lane, ADC and Support, seem to be evaluated based on criteria that complement each other. While ADC players were evaluated based on their ability to accumulate kills, Support players were evaluated on their ability to help other players and accumulate assists during fights. The fact that Support players are also heavily judged on their ability to control vision is a key component to this relationship, as controlling vision helps protecting teammates from being ambushed.

The metric that seemed universally important was the location of the player relative to a certain event. The frequent use of this criterion reflects directly the importance of the visualization of spatio-temporal information during the analysis of player performance. Furthermore, even the specific criteria used by participants from each role, are strongly related with the location of players. For instance, the HP criterion (providing help to other players) was mentioned in the context of being close to other players to help them. The AG criterion (performing ganks) is also directly associated with the location of players, because it implies that the Jungler was visiting a specific lane to help his teammates. Even the criteria related to vision strongly implies that being able to visualize the position and actions of the players on the enemy team is very important to understand player performance.

The answers given by participants, as well as their interaction strategies, indicate that there is a need to change some design implementations. The three analysis profiles identified, suggest that some users highly value the capability to create relationships between the events being shown, using the other thematic data being displayed, as well as their own game experience. Dealing with *Speculators* creates potential problems that should be addressed. Since these users create plausible scenarios based on the information they observe, adding more thematic data, especially static data, could be a valuable asset to improve these users' analysis when using the animated map. The addition of this data can potentially help these users steer towards the behavior of *Storytellers* by creating a more complete view of the status of players. If available in the future, information regarding skill usage could be incorporated in the visualization to allow users to precisely understand the actions of players. Furthermore, if the data regarding player position was available with a higher frequency, it would improve the simulated trajectories, which would translate into an analysis closer in quality to the one available through the replay system. The position of ward placements can also improve the analysis as it would provide a way of simulating the Fog of War.

Furthermore, improving the accuracy of the trajectories followed by players is paramount to allow the analysis to be as precise as possible. The direct relationship between the participants' game experience and the degree of complexity of their justifications, highlight the relevance of a solution that can be as accurate as possible and can provide as much information as possible so that it can be used in both casual and professional settings.

Considering the active role participants adopted when interacting with the animated map by using the slider, it is important to address the issues pointed out. The current implementation of the slider should be improved upon and, if possible, the suggested alternate modes of interaction should be incorporated as options that users can use to adapt their experience to their liking.

At the end of the experiment, all participants showed their interest towards VisuaLeague, having answered that they found the prototype's functionalities useful and, with respect to the animated map, innovative. The participants pointed out that they would find this approach even more useful if the measurements on the player's position as well as wards place were fully accurate to directly reflect the experience the players went through. They did not mind however, that the observed paths were simulations, mentioning that they only would like them to be more accurate. Visualizing multiple players was also heavily suggested, as it would improve on the capability of analyzing how the actions of some players could influence the performance of others. However, it's important to adapt the approach taken to display the events on the map to fix the issues with overlapping.

Finally, the results of this study suggest that users have the necessity to visualize spatio-temporal information to evaluate player performance. The technique employed, the animated map, seems to have been positively accepted by the participants as an adequate technique to visualize this type of data in the context of video games although, the current implementation need improvements.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

With the recent growth in the popularity of *e-sports*, the interest in online video games from various groups has significantly increased. This leads to various groups of individuals interesting in analyzing data related to video games, namely, players, spectators, coaches and analysts.

Because of the advancements in technology, it has become easier and more frequent to instrument video game source code with telemetry techniques to record data regarding events that take place during matches. In turn, this leads to large volumes of data that are collected over time. To efficiently and effectively analyze this data, it is necessary to study which visualization techniques are better suited for the context, while at the same time keeping in mind the requirements of users.

The work presented during this dissertation focused on the visualization of spatio-temporal data in the context of video game analysis. In particular, the developed prototype, VisuaLeague, focused on utilizing animated maps, among other techniques, to visualize player trajectory data, game events and thematic information, to help individuals evaluate the performance of players. This application used data from the game League of Legends because, due to its longevity and popularity, it provides constant stream of easily available data for analysis.

The results of the study performed suggest that the applied techniques, namely the animated maps, are highly adequate to convey spatio-temporal data to users in the context of player performance analysis in video games. Furthermore, the results show that incorporating the spatio-temporal components of data using visualization techniques, is essential when evaluating player performance.

Overall, the users demonstrate a positive attitude towards the visualization techniques applied, namely the animated map, and wish to be able to continue using these approaches to interact with spatio-temporal data during their analysis. These users can be divided in terms of the methodology of interaction with the animated map. Some users take a more passive approach and simply watch the animation unfold. Others take a more active stance and heavily interact the slider by pausing the animation multiple times and repositioning the view on the animated map. Lastly, some users take an in-between approach and passively play the animation until they decide an event needs careful attention. After that, they pause the playback and interact only by moving the slider back and forth to inspect the event in detail.

The users can also be separated into three different groups based on their analysis, namely, *Narrators*, *Storytellers* and *Speculators*. These groups differ in the complexity of the answers given when justifying the performance of players. The *Narrators* simply describe the events being observed. The *Storytellers* combine the description of the observed events, with game knowledge and experience, to create more elaborate stories to justify players performance. The *Speculators* have a behavior similar to the *Storytellers*, but often create even more elaborate stories that, although plausible, are not directly verifiable through the visualization techniques being used.

5.2 Future Work

As future work, the first issue to be addressed when using animated maps to visualize spatio-temporal data in the context of video games, should be to resolve the overlapping of events which makes it difficult to discern the situations being analyzed. One of the suggestions made by participants in the study were to aggregate events in a certain area and make them visible in chronological order when hovering over that area. Another suggestion was to place simple symbols in the map that would be mapped to a feed where detailed information about the events would be available. Following the solution to this issue, the technique should be further developed to allow users to visualize more than two players simultaneously. The current state of development of the player selection panel can be used as a starting point to implement this feature.

Reimplementing the slider to address the issues pointed out by participants during the study is also relevant to make the experience of using this technique as effortless as possible. Other important aspects to improve are, for instance, the addition of visualizations that allow the users to analyze static information, such as runes, masteries and summoner spells, as they can play an important role in understanding the choices the player makes during the game. The simulation of the paths the players take can also be improved upon by exploring more advanced techniques than the one used during development. The event filters should also be refined to grant users the ability to explicitly filter the exact events they want to observe, for example, filter towers and inhibitors destruction separately instead of as a whole.

Analyzing the paths taken by multiple players in a certain ranking range, or when using a specific champion, could also be a welcome addition by allowing users to use animated maps to analyze and compare their paths with the paths taken by more proficient players that play the same role or champion. A similar analysis could also be made to understand if certain zones of the map could be considered more dangerous than others in different stages on the game, or to understand where vision is contested more frequently. If possible, other visualizations techniques should also be explored in the context of spatio-temporal analysis of video game data.

Extracting information directly from gameplay could dramatically improve the usefulness of the techniques employed, especially the animated map. As pointed out by some participants of the study, if the information being visualized, namely, the position of the players and the position of the ward events, was more accurate, their analysis would dramatically improve. If in the future this information is provided through the API, it would enable a more frequent use of visualization techniques that take advantage of the spatio-temporal components of the data.

It could also be of interest to compare the results of this work in the context of other applications, e.g., will individuals using other applications, such as the Match History, adopt similar analysis profiles, or even speculatively mention the localization of the players in their analysis. Lastly, a paper with the results of this study will be attempted to be published in relevant venues.

Glossary

ADC - Attack Damage Carry

AJAX - Asynchronous JavaScript and XML

API - Application Programming Interface

ARTS - Action Real-Time Strategy

CMS - Construction and Management Simulation

FPS - First Person Shooter

HTTP - Hypertext Transfer Protocol

IDE - Integrated Development Environment

JSON - JavaScript Object Notation

KDA - Kills, Deaths and Assists

LS - Life Simulation

LoL - League of Legends

MFUC - Most Frequently Used Criteria

MMOGs - Massively Multiplayer Online Games

MMORPG -Massively Multiplayer Online Role-Playing Game

MOBA - Multiplayer Online Battle Arena

RPG - Role-Playing Game

SRT - Signed Rank Test

SVG - Scalable Vector Graphics

XML - eXtensible Markup Language

XP - Experience Points

Appendix A - Questionnaire

VisuaLeague

* Required

Sex *

- ◯ Male
- ◯ Female

Age *

Your answer

Field of work/study *

Your answer

Rank *

Choose

Role *

Choose

How long have you been playing League of Legends or similar games? *

Your answer

Known/Used Tools *

- ☐ Match History
- ☐ OP GG
- ☐ LoL King
- ☐ Replays
- ☐ Other:

Task #1.1

Which of the two players was the first to get killed? Did the other player participate in this event? *

Choose

Which visualizations (in order from most used to least used) did you use to answer this question? *

- [ ] Mapa
- [ ] Gold
- [ ] CS
- [ ] KDA
- [ ] Items
- [ ] Global Objectives
- [ ] Skill Order
- [ ] Other:

Task #1.2

When was the first Dragon slain? Who did it? *

Choose

On a scale from 0 - 10 evaluate the performance of both players under analysis on this event. Justify. *

Your answer

Which visualizations (in order from most used to least used) did you use to answer this question? *

- [ ] Mapa
- [ ] Gold
- [ ] CS
- [ ] KDA
- [ ] Items
- [ ] Global Objectives
- [ ] Skill Order
- [ ] Other:

Task #1.3

When and where was the first Tower destroyed? Who destroyed it? *

Choose

On a scale from 0 - 10 evaluate the performance of both players under analysis on this event. Justify. *

Your answer

Which visualizations (in order from most used to least used) did you use to answer this question? *

- [ ] Mapa
- [ ] Gold
- [ ] CS
- [ ] KDA
- [ ] Items
- [ ] Global Objectives
- [ ] Skill Order
- [ ] Other:

Task #1.4

When was the first Baron slain? Who did it? *

Choose

On a scale from 0 - 10 evaluate the performance of both players under analysis on this event. Justify. *

Your answer

Which visualizations (in order from most used to least used) did you use to answer this question? *

- [ ] Mapa
- [ ] Gold
- [ ] CS
- [ ] KDA
- [ ] Items
- [ ] Global Objectives
- [ ] Skill Order
- [ ] Other:

Task #1.5

When and where was the last Inhibitor destroyed? Who destroyed it? *

Choose

On a scale from 0 - 10 evaluate the performance of both players under analysis on this event. Justify. *

Your answer

Which visualizations (in order from most used to least used) did you use to answer this question? *

- [ ] Mapa
- [ ] Gold
- [ ] CS
- [ ] KDA
- [ ] Items
- [ ] Global Objectives
- [ ] Skill Order
- [ ] Other:

Task #2

In your opinion which of the players was ahead during the early game? Justify. *

Early Game is considered to be the portion of the game between minutes 0 and 15, around where player level varies from 1 to 9.

Your answer

In your opinion which of the players was ahead during the mid game? Justify. *

Mid Game is considered to be the portion of the game between minutes 15 and 30, around where player level varies from 9 to 14.

Your answer

In your opinion which of the players was ahead during the late game? Justify. *

Late Game is considered to be the portion of the game after 30 minutes, around where player level is above 15.

Your answer

On a scale from 0 - 10 evaluate the performance of both players under analysis during the entire game as a whole. Justify. *

Your answer

Which visualizations (in order from most used to least used) did you use to answer this question? *

- [ ] Mapa
- [ ] Gold
- [ ] CS
- [ ] KDA
- [ ] Items
- [ ] Global Objectives
- [ ] Skill Order

Final Questions

On a scale from 0 - 10 classify how important the information presented on the map was to enhance the analysis of player performance? Justify. *

Your answer

In your opinion, if the map visualization did not exist would you be able to reach the same conclusions during the previous tasks? *

Your answer

In your opinion would a global analysis (more than 2 players at once) be more beneficial to analyse player performance? *

Your answer

In your opinion is VisuaLeague useful? *

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Does VisuaLeague save time when compared to existing apps or viewing replays? *

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Does VisuaLeague meet your needs to analyse player performance during a match? *

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Is VisuaLeague easy to use? *

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Does VisuaLeague require too much effort to use? *

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Are you satisfied with VisuaLeague? *

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Is VisuaLeague fun/appellative to use? *

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Describe VisuaLeague's most positive aspects. *

Your answer

Describe VisuaLeague's most negative aspects. *

Your answer

Final thoughts/comments. *

Your answer

Appendix B – Classification Codes

Codes	Sub-Codes	ID	Description
Objective Participation		OP	The player participated in an objective
	Dragon Kill	OPD	The player killed the dragon
	Tower Kill	OPT	The player destroyed a tower
	Baron Kill	OPB	The player killed the baron
	Inhibitor Kill	OPI	The player destroyed an inhibitor
	Team Fight	OPF	The player participated in a team fight
KDA		KDA	The player's KDA was relevant
	Enemy Kill	EK	The player killed an enemy
	Death (enemy)	ED	The enemy died
	Death (self)	SD	The player died
	Death (team)	TD	A teammate died
	Assist	Ass	The player assisted in a kill
Location			
	Location (far)	LF	The player was far from the location of the observed event
	Location (alone)	LA	The player was alone at the location of the observed event
	Location (close)	LC	The player was nearby or at the location of the observed event
	Location (rotation)	LR	The player rotated to the location of the observed event (or nearby)
Vision			
	Vision	Vis	The player controlled his/her vision of the game map
	Vision (defensive)	VD	The player controlled his/her vision defensively
	Vision (lack)	VL	The player did not contribute with wards
	Vision (unawareness)	VU	The player did not had vision or any awareness of a given event
Ambush			
	Gank	AG	The player participated in the ambush of an enemy
	Gank (suffer)	AGS	The player was ganked
	Invade	AI	The player invaded the enemy jungle
Help			
	Help (provide)	HP	Player provided help to a teammate
	Help (received)	HR	Player received help
	Help (lack)	HL	Player failed to help one or more teammates
	Help (unnecessary)	HU	Player's help was not needed
Advantage			
	Advantage (null)	NA	The player had no significant advantage over the other(s)
	Advantage (player)	AP	Player had the advantage in the game (e.g., through gold, xp, or items)
	Advantage (team)	AT	Team had the advantage in the game
	Disadvantage (player)	DAP	The player was at a disadvantage at the game (e.g., through gold, xp, or items)
	Disadvantage (team)	DAT	Team was at a disadvantage at the game
	Disadvantage (mitigation)	DAM	The player/team recovered from a disadvantageous period/position
	Minimization	AM	Attempt to minimize the success of an enemy (e.g., losing an objective, couter-ganking)
Role			
	Role Error	RE	The player did not fulfil the expected actions of its role
	Role Error (others)	TS	The player's teammate(s) did not fulfil the expected actions of a certain role
	Optimal Build	OB	The player bought better items for the role
	Sub-Optimal Build	SB	The player didn't buy the best items for the role
	Character Type	CT	Champion characteristics as an explanation/description
Aggression			
	Pressure (apply)	APA	The player applied pressure over another or an objective
	Pressure (received)	APR	The player suffered pressure
	Pressure (stop)	APS	The player was able to stop being pressured (assumes the code above)
	Lack of aggression	ALA	The player was not aggressive enough
	Defend	AD	The player is defending an objective (e.g., not necessarily under pressure)
	Defend (lack)	ADL	The player is not defending an objective
	Incapacitation/Distraction	AID	The player prevented other from performing a certain action or role
	Incapacitation/Distraction (lack)	AIDL	The player did not prevent other from performing a certain action or role
Actions			
	Impact	Aimp	The player was impactful in the match/event
	Impact (lack)	Alimp	The player wasn't impactful in the match/event
	Success	Asuc	The player's action was successful
	Failure	Afail	The player's action was unsuccessful
	Consequences	Acons	A certain action contributed to another to happen
Hypothesis		Hyp	The player creates a theory to explain why something happened or what happened

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